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Research Article

Analysis of the Impact of Ride-Hailing on Urban Road Network Traffic by Using Vehicle Trajectory Data

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The growth of ride-hailing services has made people's daily commutes more convenient but has increased traffic on the road. However, the data needed to verify the impact of ride-hailing services on the urban road traffic network are lacking. This study matches data on the trajectories of different kinds of vehicles in Xuancheng city in the urban road network by using vehicle information data, ride-hailing information data, and license plate data recorded by the traffic bayonet system from December 26, 2018, to January 25, 2019. We used two indices, the detecting intensity and the detecting rate, to analyze the characteristics of travel based on ride-hailing services in Xuancheng. The results show that the ride-hailing vehicles have obvious travel characteristics of morning peak and evening peak, and in central urban areas and through the proposed indices of the travel time occupation rate and the travel space occupation rate to further quantitatively analyze the spatial and temporal characteristics of travel of different kinds of vehicles. Following this, we calculated the average ratios of different kinds of vehicles on congested sections of the road network and used simple regression to analyze the relationship between this and the average speed on these sections to quantitatively analyze the impact of ride-hailing on traffic congestion. The work here can provide effective decision-making support to the government for managing travel based on ride-hailing services.

1. Introduction

Ride-hailing [1–3] is a recently introduced travel service that has increased the convenience of daily travel. When ride-hailing services first appeared, many people had assumed that they would reduce traffic congestion [4–6]. Ride-hailing services have undergone considerable growth over the past decade. In 2018, China's DiDi Chuxing, Uber's global competitor in the industry, reported more than 450 million users and 21 million drivers. Its reported 25 million daily rides eclipsed the rides provided by the rest of the world's ride-hailing services combined [7]. The increase in the use of ride-hailing services has had a significant impact on urban traffic, and many studies have examined whether such services increase or reduce urban road congestion. Research in the area has focused on three dimensions.

The first dimension relates to the relationship between ride-hailing services and the vehicle miles traveled (VMT). An examination of the rate of occupancy and deadhead miles of ride-hailing services has shown that they may increase the total VMT. For example, a survey of Uber use by the residents of Santiago, Chile, by Tirachinia and Gomez-Lobo [8], showed that unless ride-hailing applications substantially increase their average occupancy rate for trips and institute shared or pooled ride-hailing, they will lead to an increase in the VMT. Henao and Marshall [9] used a dataset of the attributes of travel from 416 rides on Lyft, UberX, LyftLine, and UberPool, as well as travel behavior and social demographics from 311 passenger surveys to estimate that 40.8% of ride-hailing travel comprises deadhead miles, and claimed that ride-hailing leads to approximately 83.5% more VMT than otherwise. Wenzel et al. [10] used data on approximately 1.5 million individual rides provided by RideAustin in Austin, Texas, to estimate that Transportation Networking Company (TNC) drivers commuting to and from their service areas accounted for 19% of the total VMT due to ride-hailing. They also estimated that TNC drivers drove 55% more miles between ride requests within 60 minutes of each other, accounting for 26% of total VMT due to ride-hailing.

The second dimension of the impact of ride-hailing on urban traffic pertains to the relationship between it and other modes of travel. To solve the problem caused by a lack of data on the issue, researchers have examined the influence of ride-hailing on travel behavior mainly through questionnaire surveys. Some believe that ride-hailing and buses are complementary. For example, Murphy and Feigon [7] found that the higher the usage of ride-hailing services was, the more likely were people to use public transportation. However, they also claimed that the rate of use of ride-hailing services is high and largely supplements public transportation [11]. Other researchers have claimed that ride-hailing services compete with other modes of transportation. For example, Schaller [12] found that ride-hailing competes with public transit, walking, and cycling rather than with private cars in terms of use. Mucci [13] found that TNCs complement light rails but compete with buses, contributing to a 7% growth in ridership in the former and a 10% decline in the latter.

The third dimension of research on ride-hailing services is related to the analysis of changes in traffic before and after disruptions to them to explain their impact. For example, Hampshire et al. [1] studied the impact of disruptions to TNCs in Austin, Texas, in 2016—prompted by Proposition 1 being defeated—on travel behavior. They found that the disruption led 45% of the patrons of Uber and Lyft to switch to personal vehicles. Agarwal et al. [14] used high-frequency traffic data from Google Maps and found a systematic and persistent decrease in congestion in the days immediately following a citywide strike by drivers of dominant ride-hailing platforms. The magnitude of this decrease was about 40% to 53% of the reduction observed during a typical holiday.

Although the above studies have analyzed the impact of ride-hailing services on urban road traffic from different perspectives, they have many limitations. First, they have used only data on ride-hailing services (such as occupancy rate and deadhead miles) to determine that they may increase the VMT of the road network, without analyzing data on other types of vehicles. Second, the problem of an insufficient number of samples arises when using data from questionnaire surveys to study the effects of ride-hailing on road congestion. Third, some of the aforementioned studies have analyzed the effects of ride-hailing on the road network by considering disruptions to ride-hailing services. However, their analyses are based on comparisons among different periods, because of which the results contain errors and are not universally applicable. The problems of data availability and accuracy must be resolved to accurately analyze the effect of ride-hailing on urban road traffic. Some studies have examined the characteristics of vehicular travel by analyzing data on the trajectories of vehicles. For example, Zhang et al. [15] considered GPS trajectory as a major source for identifying traffic congestion and understanding the operational states of road networks. Sunderrajan et al. [16] used data on the GPS trajectories of probe vehicles to reconstruct the status of traffic. The traffic bayonet is an intelligent device commonly used in Chinese cities as an intelligent monitoring and recording system for vehicles. It

can record data based on the license plates of vehicles in real time. Ruan et al. [17] proposed an algorithm to extract vehicle trajectories based on data on license plates from the traffic bayonet system. Hu et al. [18] proposed a similar method. It is thus important to analyze data on the trajectories of different kinds of vehicles (such as those used by ride-hailing services, private cars, taxis, and buses) based on their license plate information as recorded by the traffic bayonet system. This can be used to examine their spatial and temporal characteristics of travel, and to conduct a comparative quantitative analysis.

This study makes the following contributions in comparison with past work in the area: first, the data sources used are more extensive, including data on the trajectories of ride-hailing vehicles and other types of vehicles on the roads of Xuancheng city. We obtained information on different kinds of vehicles by using license plate data recorded by the traffic bayonet system to carry out trajectory matching. This provides comprehensive support for the analysis of the comparative characteristics of travel of ride-hailing services. Second, we explain the impact of ride-hailing services on urban road traffic by applying different methods from those used in previous studies. We analyze the travel characteristics of ride-hailing by using two indices: the road network detecting intensity and the road network detecting rate of the road network. We also propose the travel time occupation rate and the travel space occupation rate of a vehicle during travel as indices to quantitatively analyze the spatial and temporal characteristics of travel of different kinds of vehicles. Finally, we calculate the average ratios of different kind of vehicles on the congested sections of the road to assess their impacts on the average speed. The work here can provide a reference for government departments to supervise ride-hailing services.

The remainder of this study is organized as follows: Section 2 introduces the source and means of matching of the data used in this paper as well as the related methods of calculation. Section 3 provides the methods used to analyze the data, and Section 4 discusses the results. Finally, Section 5 provides the conclusions of this study.

2. Data and Methods

2.1. Data. We used information on urban vehicles and ride-hailing vehicles, and the license plate data of vehicles collected by the traffic bayonet system. We matched these data using an algorithm to reconstruct vehicle trajectories. The data were collected from December 26, 2018, to January 25, 2019.

2.1.1. Raw Dataset. The first of the original datasets comprised data on vehicles in Xuancheng. They were obtained from the traffic management center database of the city that contained data on over 900,000 vehicles consisting of 844,205 private cars, 5,793 taxis, and 1,719 buses. The dataset included vehicle license plate numbers, vehicle brands, and vehicle using properties. Some examples are presented in Table 1. Part of the information is concealed for privacy-related reasons. The license plate numbers and properties of

Table 1: Information on urban vehicles.

License plate numbers	Vehicle brands	Using properties
皖PW12**	Liwei	Private car
皖PR12**	Fute	Private car
皖PTV2**	Dongfengrichan	Private car
皖PX56**	Jianghuai	Taxi
皖PC05**	Wuling	Private car
皖PP16**	Futian	Taxi
皖PA30**	Jinlong	Bus

Table 2: Information on ride-hailing vehicles.

License plate numbers	Enterprise names	Vehicle status
皖PW12**	DIDI	Operation
皖PD007**	DIDI	Operation
皖PD085**	DIDI	Cancellation
皖P5N51**	DIDI	Cancellation
皖P28B9**	DIDI	Operation
皖PD020**	DIDI	Operation
皖PD030**	DIDI	Operation

vehicle use were used to distinguish among private cars, taxis, and buses. This information was matched with the data recorded by the traffic bayonet system.

The second original dataset comprised information on ride-hailing services in Xuancheng and was obtained from the city's ride-hailing platforms. It included the license plate numbers, the names of the owing enterprise, and the status of use of 464 registered ride-hailing vehicles in Xuancheng. Some examples are presented in Table 2.

The third original dataset comprised approximately 287 million data items on all types of vehicles as recorded by bayonets at each intersection in Xuancheng. The rate of coverage of the traffic bayonet system in Xuancheng was higher than 90%. Thus, the data met the requirements of trajectory analysis. This dataset included the vehicle ID (identity), license plate numbers, properties of vehicle use, the time at which the data were recorded, intersection number at which the information was recorded, direction of the vehicle, and the number of lanes on the road. Some examples are presented in Table 3.

2.1.2. Data Matching.

Xuancheng is located in the southeast of Anhui Province and is divided into the central urban area, subcentral area, and suburbs. By 2017, the built-up area of Xuancheng spanned $65.5 \, km^2$, the total length of its roads was 191.3 km, and the proportions of the main roads, secondary roads, and branches were $1 : 1.09 : 0.16$ [19].

The ArcGIS map of roads in Xuancheng was used to match the data on the trajectories of vehicles on each section of the roads of Xuancheng. The map is shown in Figure 1 and includes the data on the centerline of the road consisting of the section number of the road, section name, starting latitude and longitude coordinates, ending latitude and longitude coordinates, and section length.

We used the structured query language (SQL) to match data on urban vehicles, ride-hailing vehicles, and vehicles recorded by traffic bayonets. This enabled the identification of the data on private cars, taxis, buses, and ride-hailing vehicles. Erroneous data recorded by the traffic bayonets were eliminated by preprocessing and cleaning them. We then considered the positional and topological relationships between road sections and traffic bayonets to eliminate erroneous data related to license plates. The travel trajectories of vehicles were obtained by finding the longest path of the coverage tree [18]. Finally, the trajectories of each kind of vehicle with different properties of use were calculated. Some examples of the data are presented in Table 4.

The locations of different kinds of vehicles on the road network were determined according to the data in Table 4. Fuzzy search methods were applied to the SQL database to determine the travel times of vehicles on each road section during a certain period. ArcGIS was used to visualize the distribution of the travel trajectories of vehicles on each section. We consider the trajectory of the vehicle with the license plate number 皖PW12 ** in Table 4 as an example. It was loaded into the ArcGIS map as shown in Figure 2. The road sections traveled by the vehicle were 1215, 1217, 1216, 1130, 1131, and 1048. Because buses have a fixed travel route, we did not perform trajectory matching for them.

2.2. Methods.

As a form of commercial travel, the travel distribution of ride-hailing services varies greatly in different periods and often appears in areas where public activities are concentrated. This causes data on the trajectories of ride-hailing vehicles to have the different characteristics of distribution on different types of roads and different regions in different periods. This can be analyzed based on the intensity and range of the data distribution. We introduce the two indices of detecting intensity [20] and detecting rate [21] to represent the distribution and range of data on the trajectories of ride-hailing vehicles, respectively. We also analyze data on the trajectories of different kinds of vehicles through data recorded by the traffic bayonets based on their license plates. This is used to calculate the spatial and temporal characteristics of travel, such as the travel time and distance, of different kinds of vehicles on the road network. Therefore, we used the two indices of the travel time occupation rate and the travel space occupation rate, which are applicable to different kinds of vehicles, are proposed in this paper. By using these two indices, we can analyze the occupancy of the spatial and temporal resources of urban road network by different kinds of vehicles such as ride-hailing vehicles, private cars, and taxis, so as to further analyze the impact of ride-hailing vehicles on urban road network traffic comparing with other types of vehicles. Because buses have fixed routes, the average detecting intensity of ride-hailing vehicles on the bus routes and other (non-bus) routes on a given day was used to reflect the characteristics of travel of ride-hailing vehicles on bus routes, so as to further analyze the impact of ride-hailing services on travel by bus. Moreover, the average ratios of different kinds of vehicles on congested sections of the road were calculated, and simple regression analysis was used to analyze the relationship between this ratio and the average speed of vehicles on

TABLE 3: Data on urban vehicles recorded by the traffic bayonet system.

Vehicle ID	License plate numbers	Using properties	Recorded time	Intersection number	Direction	Lane number
40999	皖PW12**	Private car (Ride-hailing)	2018/12/26 7:26:29	28	East	1
41000	皖PR12**	Private car	2018/12/26 7:27:03	144	South	2
41001	皖PTV2**	Private car	2018/12/26 7:34:15	32	West	3
41002	皖PX56**	Taxi	2018/12/26 7:42:22	154	North	3
41003	皖PC05**	Private car	2018/12/26 7:57:18	245	East	1
41004	皖PP16**	Taxi	2018/12/26 7:24:11	137	West	4
41008	皖PA30**	Bus	2018/12/26 7:34:14	28	East	2

- • intersection
- — road center line

FIGURE 1: ArcGIS map of road network of Xuancheng.

TABLE 4: Travel trajectory data of single vehicle.

License plate numbers	Using properties	Starting time	Ending time	Trajectory	Time (min)	Distance (m)
皖PW12**	Ride-hailing	2018/12/26 10:47:23	2018/12/26 11:02:41	1215-1217-1216-1130-1131–1048	15.3	4325
皖PR12**	Private car	2018/12/26 10:51:20	2018/12/26 11:05:08	21251-8006-15809-1213-1212	13.8	3912
皖PTV2**	Private car	2018/12/26 11:41:23	2018/12/26 11:44:38	21266–21251	3.25	1382
皖PX56**	Taxi	2018/12/26 12:39:48	2018/12/26 12:42:25	1007–1018	2.62	1016
皖PC05**	Private car	2018/12/26 12:33:48	2018/12/26 12:36:54	1031–1032	3.1	1634
皖PP16**	Taxi	2018/12/26 14:08:24	2018/12/26 14:11:24	1026–1054	3	1256

congested roads to quantify the negative impact of ride-hailing on traffic congestion.

Data on the trajectories of vehicles deliver good real-time performance. So, the statistical indices used in this paper, such as detecting intensity, detecting rate, travel time occupation rate, and travel space occupation rate, can be analyzed by smaller time granularity. These indices were calculated based on data on the trajectories of vehicles that were matched by data on their license plates as recorded by traffic bayonets at intersections. The vehicles needed to have continually passed through two or more intersections to enable matching. Therefore, the temporal granularity of the indices needed to consider the time required for vehicles to pass continuously through two intersections to ensure that a sufficient amount of data on the trajectories of vehicles was available. We set the granularity to 10 min.
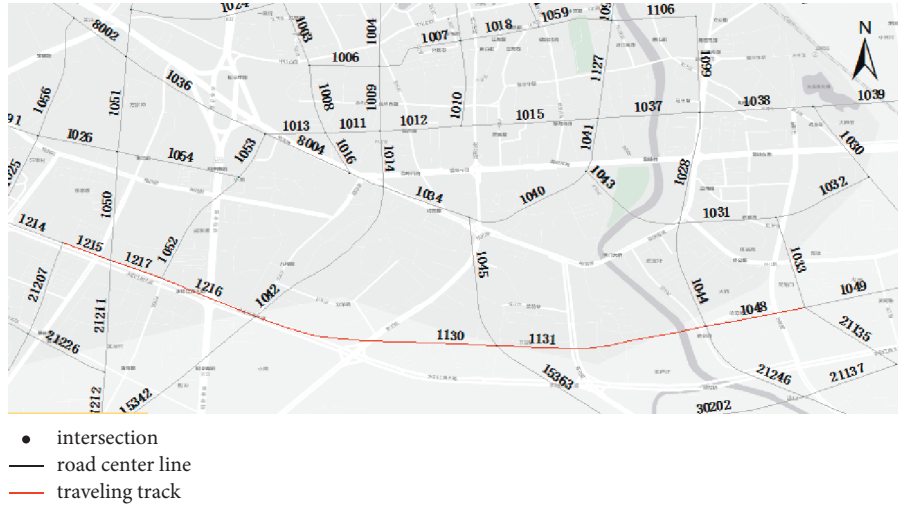
FIGURE 2: Travel trajectories of single vehicles loaded into the ArcGIS network map.

2.2.1. Models to Calculate the Detecting Intensity and the Detecting Rate of Ride-Hailing Vehicles. The detecting intensity is defined as the travel times of a vehicle on a certain road section within unit time. It is calculated as follows:

$$K_i = \frac{C_i}{T},\qquad(1)$$

where K_i is the detecting intensity of road section i (times·10 min^{-1}), C_i represents the travel times of vehicles on road section i, and T is the calculated interval (10 min).

The higher the detecting intensity of a certain road section, the more frequent the ride-hailing travel on that road section. The average value of K_i is used to determine the detecting intensity of different type of road as follows:

$$\overline{K} = \frac{\sum_{i=1}^{n} K_i}{n},\qquad(2)$$

where β is the average value of K_i and n is the number of road sections.

The detecting rate is defined as the ratio of the sum of the lengths of road sections for which the travel times of ride-hailing services meet or exceed a threshold within unit time to the total length of road sections in the network. It is calculated as follows:

$$\beta = \frac{\sum S_{Kd}}{S},\qquad(3)$$

where β is the detecting rate, S is the total length of road sections in the network (m), S_{Kd} is the length of the road section for which the travel times of the ride-hailing services meet or exceed the threshold of Kd (m), and Kd is 2 times · 10 min^{-1}, which means that the vehicle travels on a certain road section twice every 10 min.

2.2.2. Models to Calculate the Travel Time and Travel Space Occupation Rate of Vehicles. The travel time occupation rate is defined as the travel time of vehicles in the road network within unit time. It is calculated as follows:

$$\alpha_t = \frac{t}{T},\qquad(4)$$

where α_t is the travel time occupation rate (min·10 min^{-1}), t is the travel time of the vehicle in the road network (min), and T is the calculated interval (10 min).

The travel time occupation rate can be used to measure the duration of travel of vehicles in the road network. The average travel time occupation rate of different kinds of vehicles in the road network within 10 min is calculated in this paper.

The travel space occupation rate is defined as the distance traveled by the vehicle in the road network within unit time. It is calculated as follows:

$$\alpha_s = \frac{l}{T},\qquad(5)$$

where α_s is the travel space occupation rate (m·10 min^{-1}), l is the distance traveled by it in the road network (m), and T is the calculated interval (10 min).

The travel space occupation rate can be used to measure the distance of travel of vehicles in the road network. The average travel space occupation rate of different kinds of vehicles in the road network within 10 min is calculated in this paper.

2.2.3. Analysis Method of Impact of Vehicles on Congested Road Sections. By taking a single road section in the ArcGIS map as the object of analysis, the average speed on the section can be calculated using data on the trajectories of vehicles. The road section on which the average speed was less than 5 m/s was defined as a congested road section [22]. The average speed on congested road sections, the start and end times of congestion on it, the section IDs, and the numbers of different kinds of vehicles were recorded.

Data on the trajectories of vehicles located in road sections when they were congested were extracted, the numbers of ride-hailing vehicles, private cars, taxis, and buses were counted, and they were then divided by the total

number of vehicles. The average ratio of each kind of vehicle in congested road sections was thus obtained:

$$r = \frac{q}{Q}, \tag{6}$$

where r is the average ratio of different kinds of vehicles on congested road sections, q is the number of different kinds of vehicles on congested road sections (veh), and Q is the total number of vehicles (veh).

The above was used to quantify the impact of the average ratio r of ride-hailing vehicles, private cars, taxis, and buses on the average speed V of the congested road section by simple regression analysis. Linear fitting graphs of r and V were drawn using Origin software. If the correlation coefficient R of r and V was greater than the threshold value R_{n-2}, this showed a significant correlation between r and V. The impact of ride-hailing vehicles and other types of vehicles on congested road sections was then quantitatively analyzed by fitting the linear equations of r and V.

3. Results

3.1. Analysis of Travel Characteristics of Ride-Hailing Vehicles in the Road Network.
Owing to the different traffic flows on working days and holidays, it was necessary to analyze the characteristics of travel of ride-hailing services on both sets of days. We thus used data on a working day (Thursday, January 10, 2019) and a holiday (Sunday, January 13, 2019) for calculation.

3.1.1. Analysis of the Detecting Intensity of Ride-Hailing Vehicles in the Road Network.
The average detecting intensity of ride-hailing vehicles over a 24-hour period in the road network was calculated for the working day and the holiday by using (1) and (2). The results are presented in Figure 3.

As displayed in Figure 3, the detecting intensity of ride-hailing vehicles in the road network has obvious characteristics of morning peak and evening peak on the working day. The morning peak began at 7:00 and lasted until 10:30, reaching its peak value at 10:10. The evening peak began at 16:50 and lasted until 19:00, reaching its peak value at 17:30. The detecting intensity of ride-hailing vehicles on each road section was relatively stable during flat peak hours. On the holiday, the peak detecting intensity began at 12:50 and lasted until 19:30, reaching its peak value at 14:00.

The grade of the road also had a significant impact on the detecting intensity of ride-hailing vehicles. The detecting intensity on high-grade roads, such as expressways, is higher by more than 10 times·10 min^{-1} during peak hours. However, the detecting intensity of ride-hailing vehicles was low on low-grade roads, less than two times·10 min^{-1}. This result was obtained mainly because of the large number, wide coverage, and poor conditions of low-grade roads. The demand for travel of ride-hailing vehicles on low-grade roads was lower than that on high-grade roads.

3.1.2. Analysis of Detecting Rate of Ride-Hailing Vehicles in the Road Network.
The detecting rate of ride-hailing vehicles over a 24-hour period on different types of roads was calculated using Equation (3). The results are shown in Figure 4.

The detecting rate of ride-hailing vehicles on high-grade roads (expressways and arterial roads) was higher than that on low-grade roads (secondary roads and branch roads), which indicates that these vehicles were mainly distributed on high-grade roads. Moreover, the detecting rate of ride-hailing vehicles varied with the grade of the road. High-grade roads had a higher detecting rate, which indicates that the trajectories of ride-hailing vehicles were mainly concentrated on urban expressways and arterial roads. The variation in the detecting rate of ride-hailing vehicles on different types of roads on the holiday was similar to that on the working day: the peak was relatively delayed and was slightly higher than that on the working day.

The data on the travel times of ride-hailing vehicles within Xuancheng from December 26, 2018, to January 25, 2019, were loaded into the ArcGIS map of the road network of the city (Figure 5).

The detecting rate of ride-hailing vehicles was calculated for each area of Xuancheng by using Equation (3). The average rate in the central area was approximately 23.41% higher than that in the subcentral areas and 30.32% higher than that in the suburbs.

3.2. Comparative Analysis of Spatial and Temporal Characteristic of Travel of Different Kinds of Vehicles

3.2.1. Analysis of Travel Time Occupation Rate of Ride-Hailing Vehicles, Private Cars, and Taxis.
Data from one working day (Thursday, January 10, 2019) and one holiday (Sunday, January 13, 2019) were selected for this calculation. Equation (4) was used to calculate the travel time occupation rate over a 24-hour period for ride-hailing vehicles, private cars, and taxis. The results are presented in Figure 6.

As shown in Figure 6, the average travel time occupation rate of ride-hailing vehicles began to rise sharply from 7:00 and reached its peak at 10:10. The peak period lasted for 3 hours and 10 minutes. After a short and flat peak at around noon, the curve rose again and reached its peak value at 17:00. During the holiday, the peak began at 7:30 and lasted until 18:30, for 11 hours and reached its peak value at 13:50. The peak period lasted longer on the holiday than on the working day. The average travel time occupation rate differed significantly between ride-hailing vehicles and private cars: 4.24 min·10 min^{-1} and 0.37 min·10 min^{-1} in the peak periods, respectively. The average travel time occupation rate of ride-hailing vehicles on the working day and the holiday was 14.49 and 14.43 times greater than that of private cars, respectively. In comparison with taxis, the average travel time occupation rate of ride-hailing was higher only in the morning and evening peak hours. From 11:00 to 14:50 and 21:20 to 7:00 on the working day, and from 11:00 to 13:30 and 23:00 to 8:30 on the holiday, the average travel time occupation rate of taxis was higher than that of ride-hailing vehicles. At night, the average travel time occupation rate of taxis was approximately 10 times higher than that of ride-hailing vehicles, which indicates that ride-hailing was rarely used for travel at night.
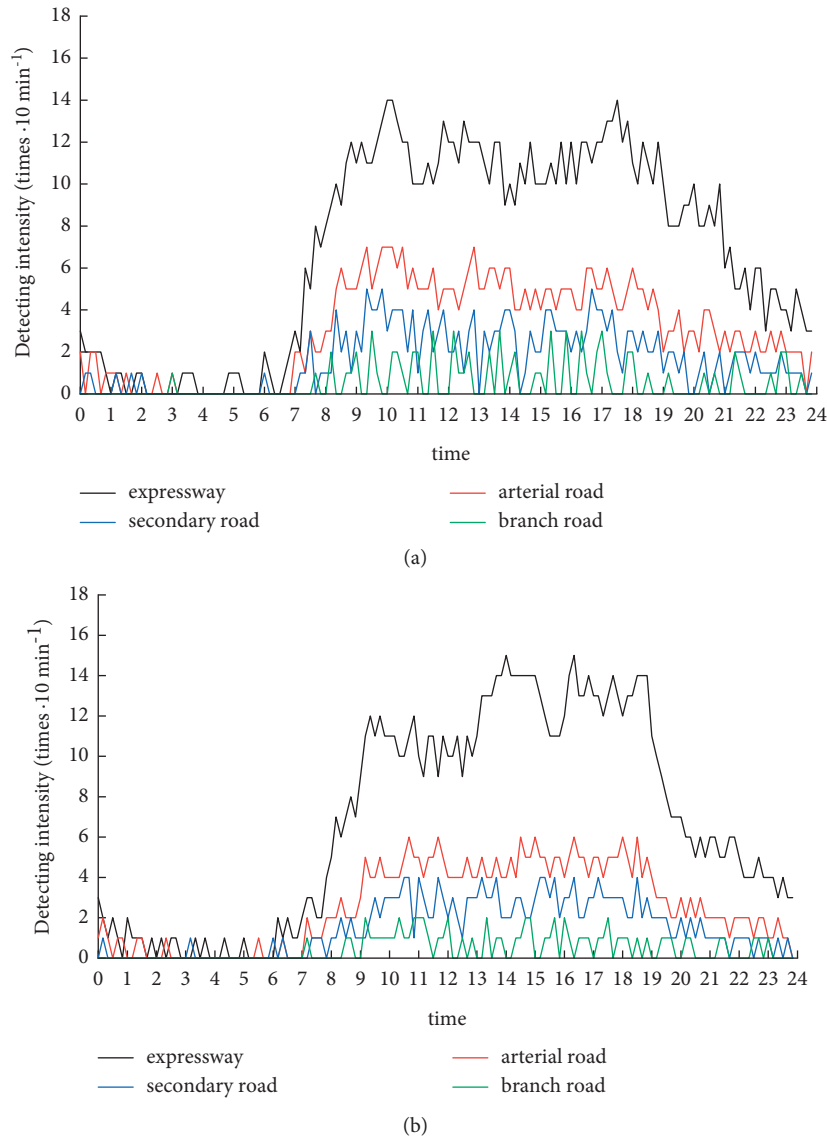
(a)

(b)

FIGURE 3: Detecting intensities of ride-hailing vehicles on a working day and a holiday. (a) Working day. (b) Holiday.

3.2.2. Analysis of Travel Space Occupation Rate of Ride-Hailing Vehicles, Private Cars, and Taxis. The data for one working day (Thursday, January 10, 2019) and one holiday (Sunday, January 13, 2019) were selected for calculation. Equation (5) was used to calculate the travel space occupation rate over a 24-hour period. The results are presented in Figure 7.

As displayed in Figure 7, variations in the average travel space occupation rate of ride-hailing vehicles on the working day were similar to the average travel time occupancy rate. The morning peak began at 7:10 and lasted until 11:30 for 4 hours and 20 minutes, reaching the peak value at 9:40. The evening peak began at 16:30 and lasted until 19:10 for 2 hours and 40 minutes, reaching its peak value at 17:00. The average travel space occupation rate of ride-hailing vehicles during the peak period was relatively stable. The peak on the holiday appeared at 7:00 but lasted longer than on the working day. Compared with private cars, ride-hailing vehicles had a higher travel space occupation rate. The average

travel space occupation rate of ride-hailing vehicles ($970 \, m \cdot 10 \, min^{-1}$ and $980 \, m \cdot 10 \, min^{-1}$ on the working day and the holiday, respectively) was considerably higher than that of private cars ($90 \, m \cdot 10 \, min^{-1}$ and $75 \, m \cdot 10 \, min^{-1}$, respectively). Their average rates were 14.32 and 14.07 times higher than those of private cars on the working day and the holiday, respectively. The peak of the travel space occupation rate of taxis lasted from 11:30 to 16:30, with the peak value appearing at 14:00. This period represents flat peak hours, and the average travel space occupation rate of taxis was higher than that of ride-hailing vehicles during it. The average rate of taxis was also higher than that of ride-hailing vehicles from 22:10 to 6:50 (at night/early morning), whereas the average rate of ride-hailing vehicles was higher than that of taxis in the morning and evening peak hours.

3.2.3. Analysis of Impact of Ride-Hailing Vehicles on Travel by Bus. (1) Analysis of Average Detecting Intensity of Ride-
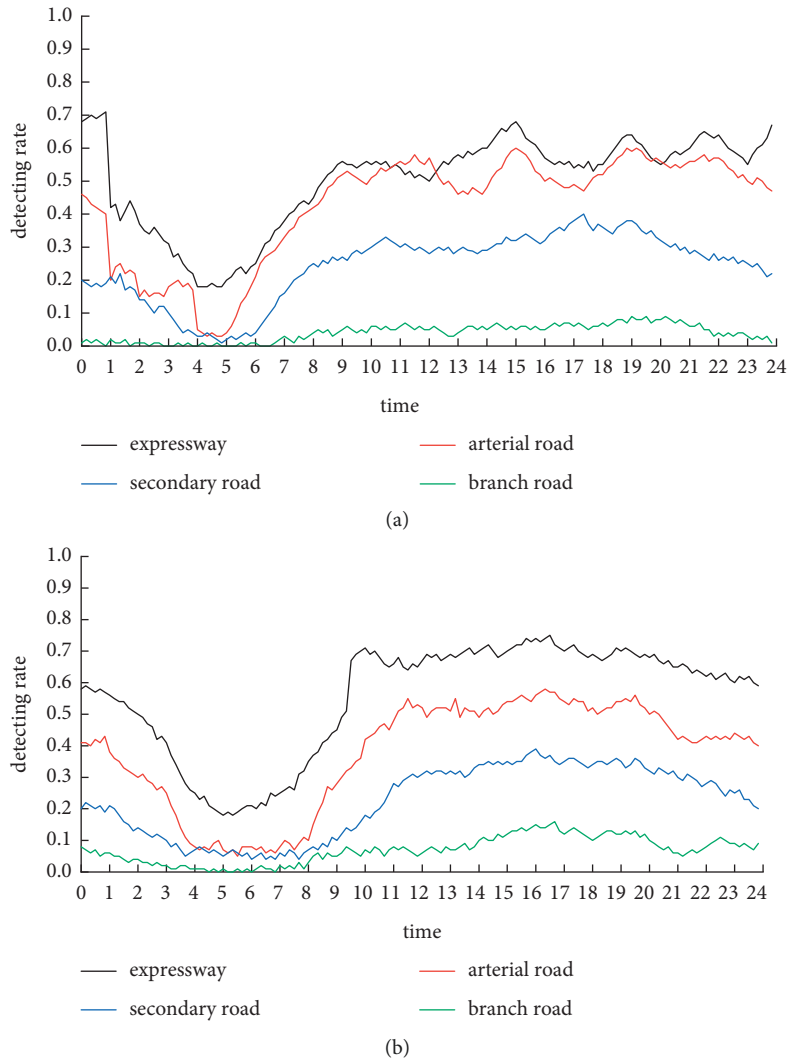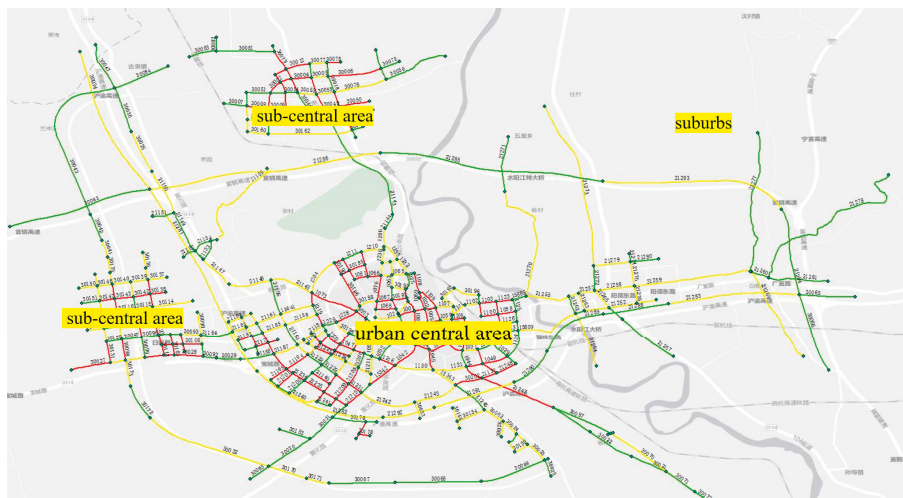
(a)

(b)

FIGURE 4: Detecting rate of ride-hailing vehicles on different types of roads. (a) Working day. (b) Holiday.

FIGURE 5: Data distribution of travel times of ride-hailing vehicles in each area of Xuancheng.
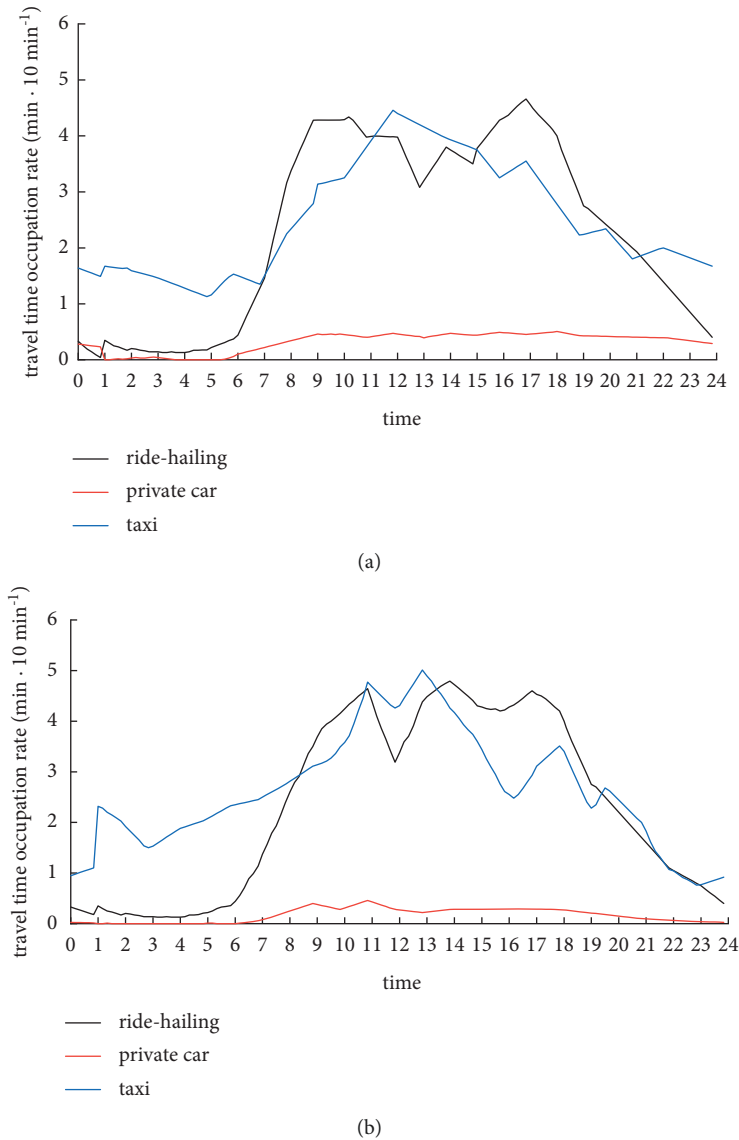
(a)

(b)

FIGURE 6: Average travel time occupation rate of ride-hailing vehicles, private cars, and taxis. (a) Working day. (b) Holiday.

Hailing on Bus and Non-Bus Routes. The main bus routes of Xuancheng are shown in Figure 8.

The data for a working day (Thursday, January 10, 2019) and a holiday (Sunday, January 13, 2019) were selected once again for calculation. The average detecting intensity of ride-hailing vehicles on bus and non-bus routes was calculated for a 24-hour period by using (1) and (2). The results are presented in Figure 9.

As displayed in Figure 9, the average detecting intensity of ride-hailing vehicles on bus routes was generally higher than that on non-bus routes. From 08:30 to 19:30 on the working day, the average detecting intensity of ride-hailing vehicles on bus routes was 1.6 times·10 min^{-1} higher than that on non-bus routes. Similarly, this intensity began to rise sharply at 07:40 on the holiday. The growth in the detecting intensity tended to be flat at 08:30 and reached its peak value at 12:30. The peak appeared again at 18:30. Moreover, the average detecting intensity of ride-hailing vehicles on bus

routes on the holiday is 1.3 times·10 min^{-1}–2.5 times·10 min^{-1} higher than that on non-bus routes.

(2). Analysis of the Travel Times of Ride-Hailing Vehicles on Bus Routes. The travel times of ride-hailing vehicles on bus routes from December 26, 2018, to January 25, 2019, are shown in Table 5.

The data of travel times of ride-hailing vehicles on bus routes were loaded into the ArcGIS map of the main bus routes in Xuancheng (Figure 10).

Figure 10 shows that Xuancheng's bus routes were dense in the central area of the city. The data distribution of the travel times of ride-hailing vehicles on bus routes in Xuancheng showed a trend of gradual weakening from the central area to the suburbs. The statistical data in Table 5 shows that the average travel times of ride-hailing vehicles on bus routes in the central area were two times higher than those in the subcentral areas and about six times higher than those in the suburbs.
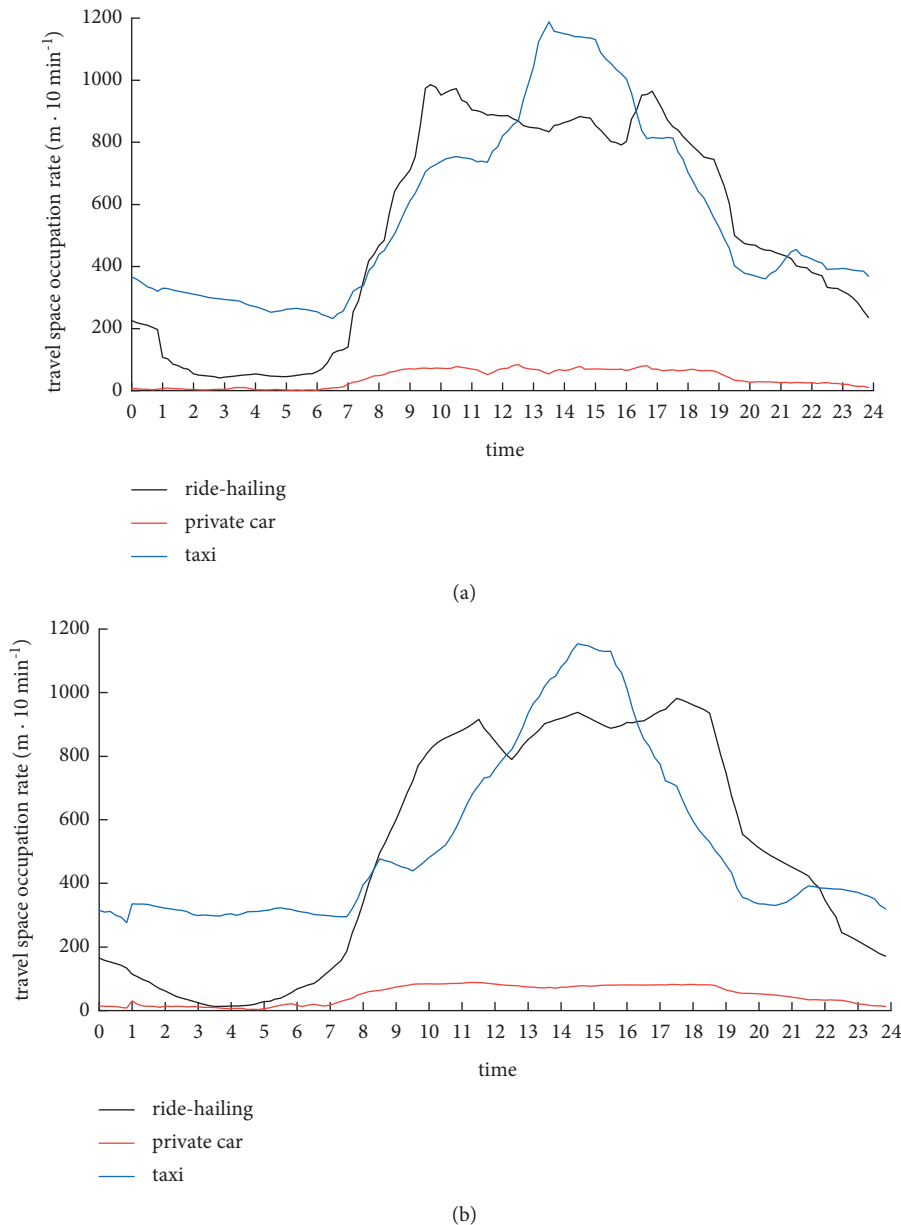
(a)

(b)

FIGURE 7: Average travel space occupation rate of ride-hailing vehicles, private cars, and taxis. (a) Working day. (b) Holiday.

3.3. Analysis of Impact of Vehicles on Congested Road Sections. We examined 20 congested road sections on which the average speed of vehicles was less than 5 m/s during a working day (Thursday, 10 January 2019). We calculated the average ratios of ride-hailing vehicles, private cars, taxis, and buses on congested road sections by Equation (6). The results are shown in Table 6.

It can be seen from Table 6, the total number of private cars was the largest, reaching to 844205, and the number of private cars on the congested road sections was also the largest, which was 2238, but the average ratio of private cars on congested road sections is the lowest, with an average of 0.000133. The total number of ride-hailing vehicles was the smallest, only 464. However, the number of ride-hailing vehicles on congested road sections was the largest after

private cars, 335. The average ratio of ride-hailing vehicles in the congested road sections was the highest, with an average of 0.0361. Although the number of taxis on the congested road sections was greater than that of buses, the average ratios of taxis and buses were close, at 0.0011 and 0.0014, respectively. A comparison of the average ratios of different kinds of vehicles on congested road sections showed that the average ratio of ride-hailing vehicles was 271.4 times higher than that of private cars, 32.8 times higher than that of taxis, and 25.8 times higher than that of buses. This indicates that the frequency of travel of ride-hailing vehicles on congested road sections was the highest of all types of vehicles.

The average speed V on congested road sections and the average ratio r of different kinds of vehicles in Table 6 were analyzed by simple regression. Origin software was used to
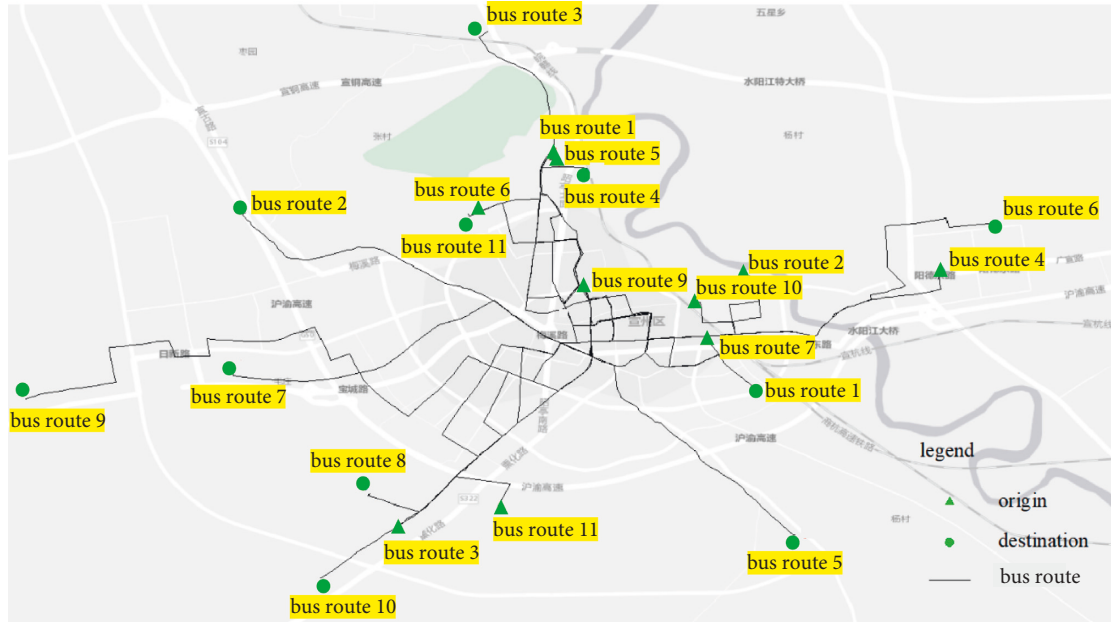
FIGURE 8: ArcGIS map of main bus routes in Xuancheng.

draw the graphs of linear fitting of r and V, which are shown in Figure 11.

Figure 11 shows that the correlation coefficients R of the graph of linear fitting of ride-hailing vehicles, private cars, taxis, and buses were −0.931, −0.968, 0.322, and 0.430, respectively. When n was 20, $R_{n-2} = 0.444$ [23]. Because the absolute value of R corresponding to ride-hailing vehicles and private cars was greater than R_{n-2}, there was a significant negative correlation between the average ratios r of ride-hailing vehicles and private cars on congested road sections, and the average speed V on these sections. The absolute values of R for taxis and buses were less than R_{n-2}, and thus, there was no clear linear correlation between the average ratios r of taxis and buses on congested road sections, and the average speed V on them. This shows that ride-hailing vehicles and private cars had a significant negative impact on the average speed on congested road sections. The equations of linear regression corresponding to ride-hailing vehicles and private cars in Figure 11 show that when their numbers increased by one on a congested road section, their respective average ratios increased by 1/464 and 1/844205, and their average speeds on the corresponding congested road section decreased by 0.42 m/s and 0.02 m/s. That is, the impact of the average ratio of ride-hailing vehicles on the average speed on congested road section was 21 times greater than that of private cars. The average ratios of taxis and buses had no significant impact on the average speed on congested road sections.

4. Discussion

4.1. Characteristics of Travel of Ride-Hailing Vehicles in the Road Network. Figure 3 shows that the detecting intensity of ride-hailing vehicles on the working day has obvious characteristics of morning peak and evening peak. The morning peak began at 7:00 and lasted until 10:30, and the evening peak began at 16:50 and lasted until 19:00. These periods are the main commuting hours in Xuancheng. This result agrees with the opinion of Agarwal, who claimed that ride-hailing vehicles have the strongest effect on congestion in the road network during peak commuting hours. The service times of ride-hailing vehicles might be the highest during peak commuting hours on a normal day [14]. This is also in agreement with Dong, who analyzed the travel data of DiDi and claimed that the peak travel using ride-hailing vehicles occurred during the peak commuting periods: 07:30–09:30 and 16:30–18:30 [10]. As shown in Figure 4, the detecting rate of ride-hailing vehicles was higher on urban high-grade roads than that on low-grade roads, which indicates that they had a large distribution on the former and a small distribution on the latter. The data in Figure 5 indicate that the detecting rates of ride-hailing vehicles in the central area of Xuancheng were approximately 23.41% and 30.32% higher than those in the sub-central areas and suburbs, respectively. Thus, ride-hailing services are mostly used in the urban central area and on high-grade roads of the city. This phenomenon might have occurred owing to the high population density, job concentration, and demand for travel in the central area. This finding agrees with the opinion of Zhang, who proposed that Chengdu's ride-hailing travel was relatively concentrated in areas close to the city center, and mainly on the expressway of the second ring road [24]. It is also similar to the view expressed by Lee, who proposed that ride-hailing vehicles are likely to increase traffic congestion in the central areas of cities [25].

4.2. Spatial and Temporal Characteristics of Travel of Ride-Hailing Vehicles and Other Types of Vehicles. Figure 6 shows that the average travel time occupation rate of ride-hailing
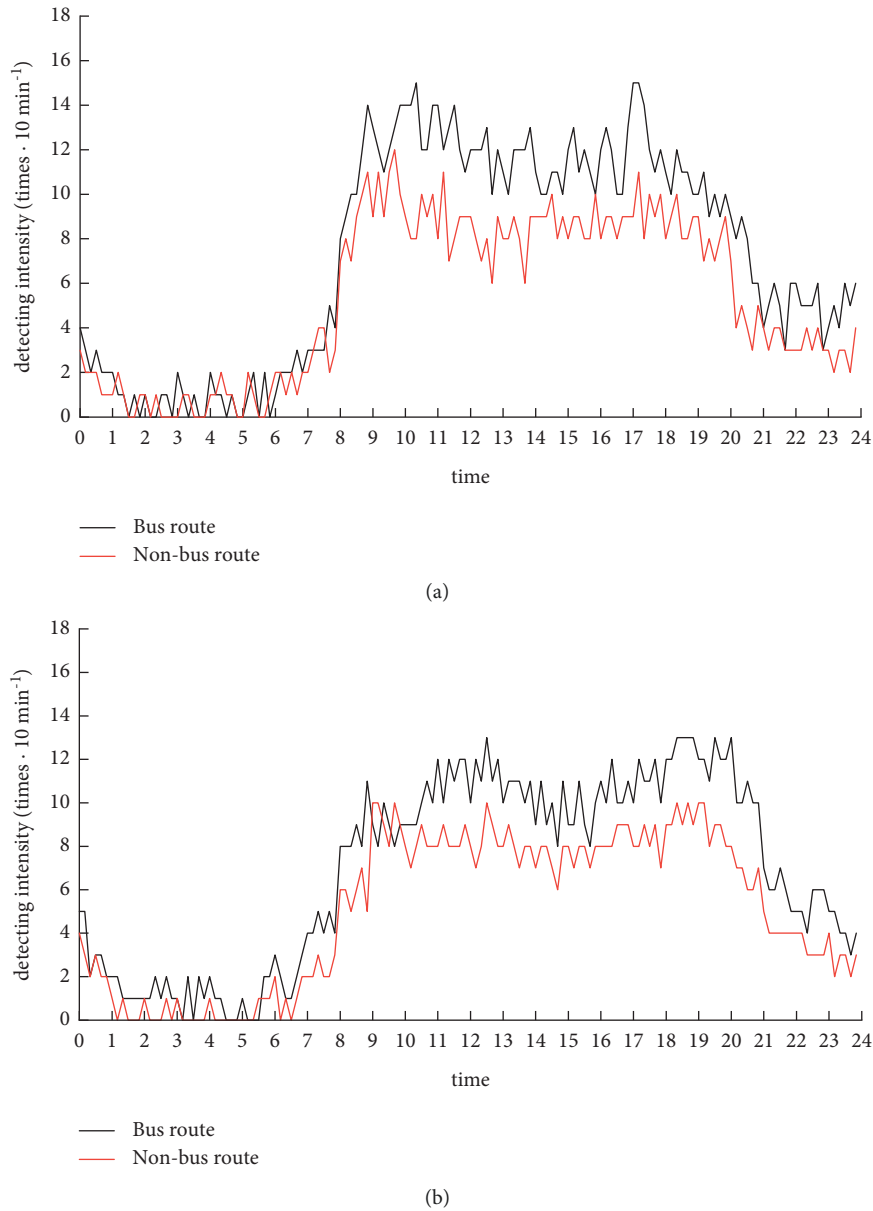
(a)

(b)

FIGURE 9: Average detecting intensity of ride-hailing vehicles on bus and non-bus routes. (a) Working day. (b) Holiday.

TABLE 5: The travel times of ride-hailing vehicles on bus routes in Xuancheng.

Area	Numbers of road sections for bus routes	Total travel times	Average travel times
Central area	118	408162	3459
Subcentral areas	6	10452	1742
Suburbs	47	23406	498

vehicles was 14.49 and 14.43 times higher than that of private cars on the working day and the holiday, respectively. Figure 7 shows that the average travel space occupancy rate of ride-hailing vehicles was 14.32 and 14.07 times higher than that of private cars on the weekday and the holiday, respectively. Therefore, ride-hailing vehicles exert greater pressure on the road network than private cars. This phenomenon arose possibly because the characteristics of travel

of ride-hailing vehicles are different from those of private cars. The main function of ride-hailing vehicles is to transport passengers for profit, and thus, they have a relatively long whole-day travel time. The main function of private cars is to meet the owners' travel needs, because of which they have a relatively short whole-day travel time. If people's travel demands led to a shift from the use of private cars to ride-hailing vehicles, a greater reduction in the

(Travel times of ride-hailing)
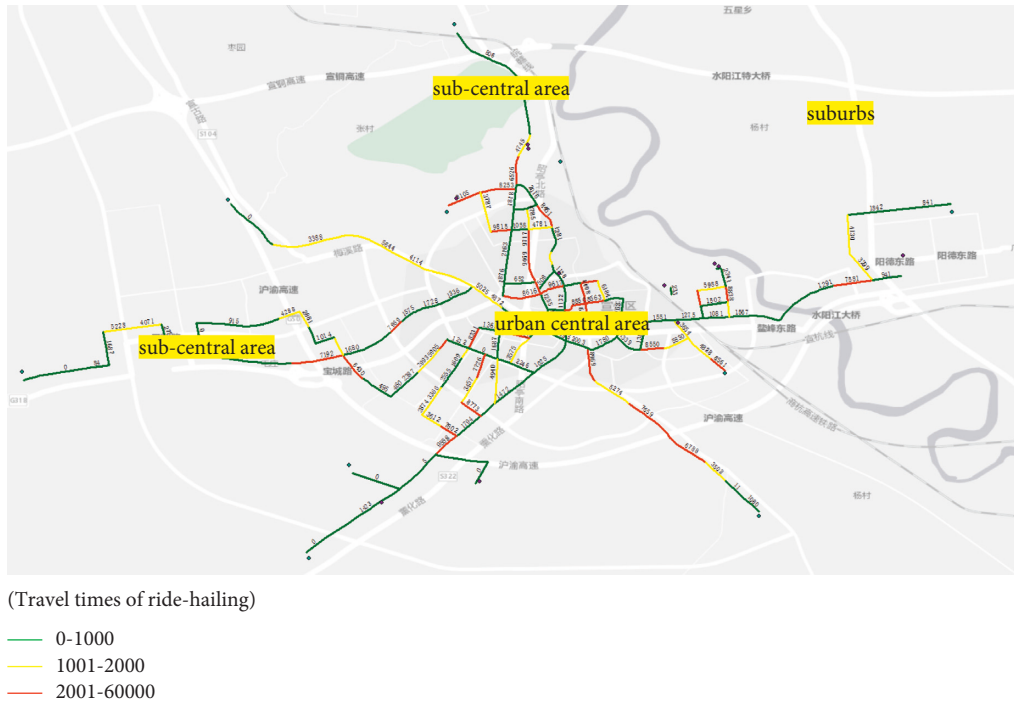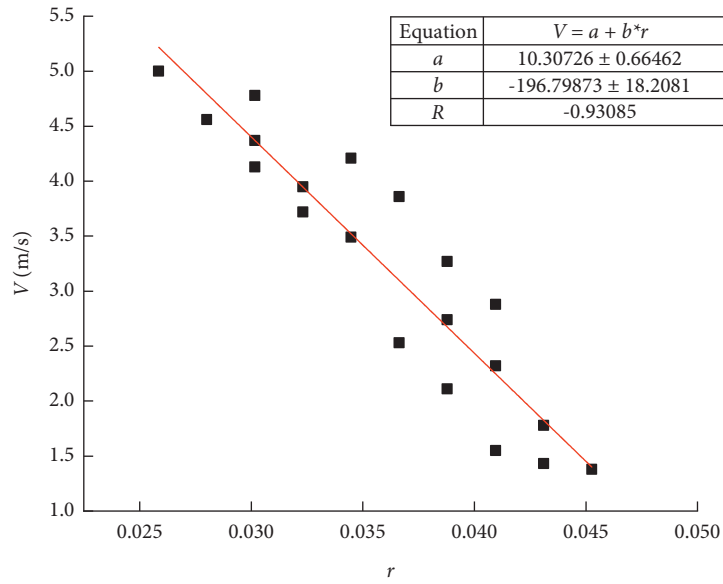
—— 0-1000
—— 1001-2000
—— 2001-60000

FIGURE 10: Data distribution of travel times of ride-hailing vehicles on bus routes.

TABLE 6: Average ratios of different kinds of vehicles on congested road sections.
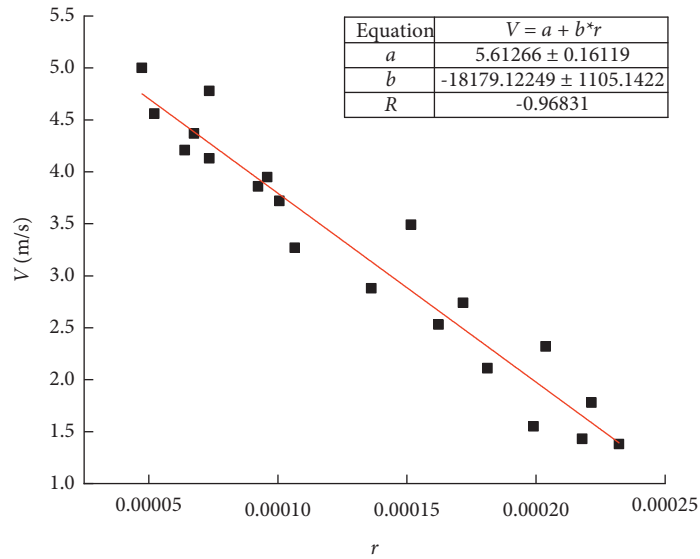
Road section ID	Start time	End time	Average speed	Ride-hailing vehicles			Private cars			Taxis			Buses		
				q	Q	r	q	Q	r	q	Q	r	q	Q	r
1005	8:21:15	8:30:07	5	12		0.0259	40		0.000047	10		0.0017	4		0.0023
1031	8:22:37	8:35:22	4.78	14		0.0302	62		0.000073	8		0.0014	2		0.0012
1067	8:32:56	8:42:39	4.56	13		0.0280	44		0.000052	4		0.0007	3		0.0017
1216	8:33:27	8:44:13	4.37	14		0.0302	57		0.000068	6		0.0010	2		0.0012
1040	8:38:29	8:52:07	4.21	16		0.0345	54		0.000064	9		0.0016	3		0.0017
1036	8:41:24	8:53:06	4.13	14		0.0302	62		0.000073	7		0.0012	2		0.0012
1042	8:42:54	9:01:44	3.95	15		0.0323	81		0.000096	5		0.0009	3		0.0017
1048	8:51:27	9:06:09	3.86	17		0.0366	78		0.000092	6		0.0010	2		0.0012
21135	8:53:06	9:09:48	3.72	15		0.0323	85		0.000101	4		0.0007	3		0.0017
1037	8:58:19	9:24:23	3.49	16	464	0.0345	128	844205	0.000152	8	5793	0.0014	2	1719	0.0012
1045	17:48:54	18:01:57	3.27	18		0.0388	90		0.000107	5		0.0009	3		0.0017
21246	17:51:09	18:13:01	2.88	19		0.0409	115		0.000136	9		0.0016	4		0.0023
1217	17:56:12	18:22:03	2.74	18		0.0388	145		0.000172	7		0.0012	2		0.0012
1051	18:01:02	18:23:08	2.53	17		0.0366	137		0.000162	6		0.0010	3		0.0017
1010	18:05:04	18:32:09	2.32	19		0.0409	172		0.000204	6		0.0010	1		0.0006
1208	18:06:27	18:33:29	2.11	18		0.0388	153		0.000181	4		0.0007	2		0.0012
1059	18:12:09	18:44:06	1.78	20		0.0431	187		0.000222	8		0.0014	1		0.0006
1004	18:15:37	18:44:34	1.55	19		0.0409	168		0.000199	6		0.0010	3		0.0017
1024	18:16:28	18:46:48	1.43	20		0.0431	184		0.000218	5		0.0009	2		0.0012
15342	18:23:24	18:54:51	1.38	21		0.0453	196		0.000232	4		0.0007	1		0.0006
				Average		0.0361	Average		0.000133	Average		0.0011	Average		0.0014

number of private cars than the increase in the number of ride-hailing vehicles will occur on the road network as the latter can be shared by several people. However, while ride-hailing vehicles can be shared by up to four people in theory, their actual rate of occupancy is much lower: 1.4 passengers per ride [9]. Given that the average rates of temporal and spatial occupancy of ride-hailing vehicles are more than 14 times those of private cars, their use instead of that of private cars will impose greater pressure on the road network that is likely to cause more traffic congestion. This finding agrees with the opinion of Tirachini, who proposed that unless ride-hailing services substantially increase their average rate of occupancy during trips and become shared or pooled vehicles, they will lead to an increase in the VMT [8]. This also
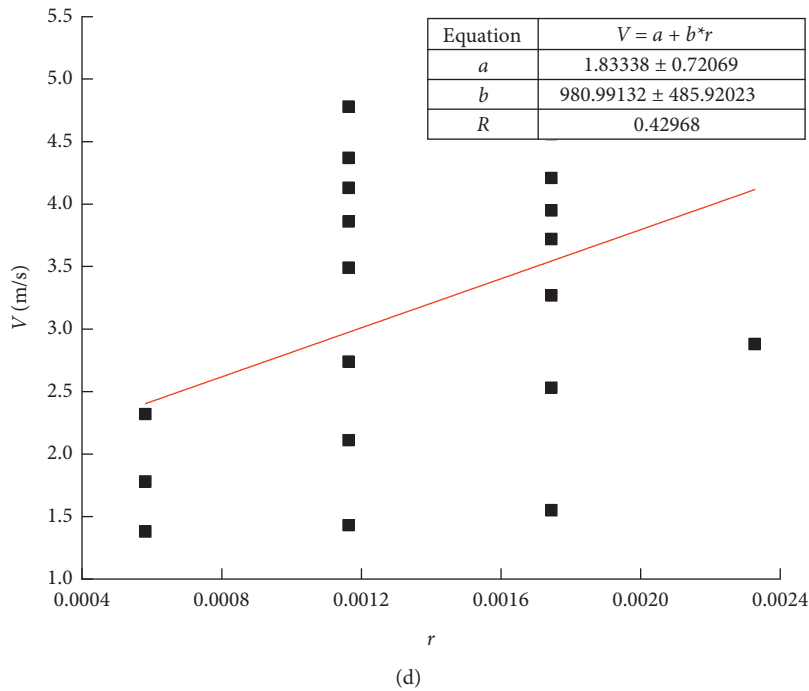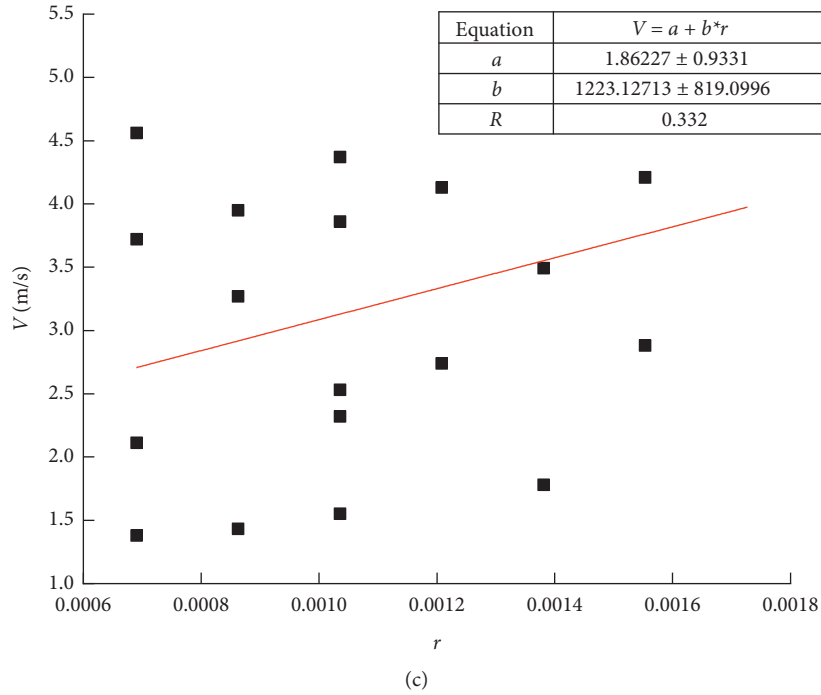
(a)

(b)

FIGURE 11: Continued.

Equation	$V = a + b*r$
a	1.86227 ± 0.9331
b	1223.12713 ± 819.0996
R	0.332

(c)

Equation	$V = a + b*r$
a	1.83338 ± 0.72069
b	980.99132 ± 485.92023
R	0.42968

(d)

FIGURE 11: Graphs of linear fitting of r and V. (a) Ride-hailing vehicles. (b) Private cars. (c) Taxis. (d) Buses.

agrees with the opinion of Henao, who proposed that the deadhead distance of ride-hailing vehicles was 40.8% of their total distance traveled. This can lead to traffic congestion. However, our result is different from that reported by Shoup, who claimed that ride-hailing vehicles significantly reduce, or eliminate altogether, the time and distance traveled in search of parking and thus reduce congestion [26]. Therefore, we think that it is important for the government to limit the number of ride-hailing vehicles and focus on improving their rate of occupancy.

Figures 6 and 7 show that the average travel time occupation rate and the average travel space occupation rate of ride-hailing vehicles were higher than those of taxis during the commuting hours of morning peak and evening peak. The travel peak of taxis occurred from 11:30 to 16:30, which indicates that ride-hailing vehicles have a stronger impact on the road network than taxis during peak commuting hours. Ride-hailing platforms provide rewards for drivers traveling during peak hours [27], whereas taxi drivers may refuse to pick up passengers during peak hours because they are

unwilling to travel on congested roads [28]. This finding verifies the analysis of Fu and Cheng on the travel characteristics of taxis. Fu used GPS data on taxis to claim that many taxi drivers were unwilling to carry passengers in the central area of Shanghai during the morning peak hours that involve serious traffic congestion and that there were fewer taxis in this area. After the morning peak hours, taxis began to enter this area, and their number peaked between 13:00 and 16:00 [29]. By analyzing the OD data of taxis, Cheng proposed that the peak taxi travel occurred between 14:00 and 15:00 in Beijing. Therefore, passengers prefer to use ride-hailing services rather than taxis during peak hours. The more opportunities there are for ride-hailing vehicles to travel during peak hours, the greater their deadhead distance is [30], and the greater is the pressure on the road network during peak hours. This finding supports the views of SFCTA, Contreras, and Paz, whereby ride-hailing services may result in a significant reduction in the number of passengers in taxis, and a longer deadheading distance generated by ride-hailing vehicles results in more serious traffic jams [10]. Therefore, government departments should introduce policies to encourage travel by taxis in peak hours.

Figure 9 shows that the detecting intensity of ride-hailing vehicles on bus routes was 1.6 times·10 min^{-1} higher than that on non-bus routes on average. Figure 10 shows that the average travel times of ride-hailing vehicles on bus routes in the central area of Xuancheng were two times higher than those in the subcentral area, and about six times higher than those in the suburbs. Thus, there may be a competitive relationship between ride-hailing vehicles and buses in the central area of Xuancheng. This suggests in turn that the dense bus route network in the central area does not induce residents to choose public transit, and a large part of their travel demands are fulfilled by ride-hailing vehicles. This may be because ride-hailing vehicles are cheaper than taxis, and more convenient and private than buses. As the travel times of ride-hailing vehicles increase, the rate of occupancy of public transit decreases, and this may lead to traffic congestion. This finding agrees with the opinions of Clewlow and Agarwal, who claimed that ride-hailing vehicles are a competitor to bus services and exacerbate traffic congestion [3, 14]. The detecting intensity of ride-hailing vehicles on bus routes leading to noncentral areas of Xuancheng was lower, and this suggests that people prefer to use buses over ride-hailing services because of the long travel distance to reduce cost. Therefore, ride-hailing services and bus services may have a complementary relationship along bus routes leading to the noncentral areas: after having traveled a long distance to arrive at a bus station, passengers can choose ride-hailing services to reach their final destination, which is presumably relatively close. This finding supports the views of Li, who claimed that ride-hailing vehicles can be used as a supplementary mode of public transportation during interregional journeys [31].

4.3. Impact of Vehicles on Congested Road Sections. The average ratio of ride-hailing vehicles was the highest on congested road sections on the working day and was 271.4 times, 32.8 times, and 25.8 times higher than that of private cars, taxis, and buses, respectively. Simple regression analysis showed a significant, linear, and negative correlation between the average ratios of ride-hailing vehicles and private cars, and the average speed on the corresponding congested road section. The average ratio of ride-hailing vehicles had the greatest impact on the average speed on the congested road sections, 21 times greater than that of private cars. When the number of ride-hailing vehicles increased by one on a congested road section, the average speed on the section decreased by 0.42 m/s. Taxis and buses had no prominent impact on the average speed on congested road sections.

As described in Section 4.1, ride-hailing vehicles have obvious travel characteristics of morning peak and evening peak, when more sections of the road were congested, and this had the greatest impact on speed on these sections. On the contrary, although the number of private cars was the largest, a single car generally makes a single trip on a congested road section, because of which its average frequency of travel on it is the lowest. However, the large number of private cars in peak hours also has a negative impact on speed on congested roads. Moreover, taxi drivers are unwilling to travel in the congested period, and the number of buses is small, and their routes are fixed. Therefore, the average frequencies of travel of taxis and buses on congested road sections were far lower than those of ride-hailing vehicles, and thus they did not have a direct impact on speed on these roads. This finding agrees with the opinion of Agarwal, who claimed that periods of strikes by drivers of ride-hailing services correspond to significant drops in delays, with the greatest reduction observed on the busiest routes during peak hours [14].

5. Conclusion

In this paper, the authors matched data on the trajectories by obtaining the information data of different kinds of vehicles (ride-hailing vehicles, private cars, taxis, and buses) and the license plate data recorded by the traffic bayonet system. The characteristics of travel of ride-hailing vehicles were analyzed, and their impact on congested roads were quantitatively compared with those of other kinds of vehicles. The results show that ride-hailing vehicles have a more significant impact on urban road traffic than the other types of vehicles. First, the ride-hailing vehicles have obvious travel characteristics of morning peak and evening peak, and in central urban areas. Moreover, these vehicles mainly traveled on urban expressways and arterial roads. Second, the average travel time and travel distance of ride-hailing vehicles were more than 14 times higher than those of private cars, which indicates that they have a greater impact on road traffic in Xuancheng. When the frequency of ride-hailing vehicles was sufficiently high, they were likely to cause traffic congestion. Third, the average travel time occupation rate and the average travel space occupation rate of ride-hailing vehicles were higher than those of taxis in the morning and evening peak hours. Therefore, they had a greater impact than taxis on traffic in Xuancheng during peak commuting hours. An increase in the frequency of travel of ride-hailing vehicles may reduce opportunities for taxis to pick-up

passengers during peak commuting hours. Fourth, a competitive relationship existed between ride-hailing vehicles and bus services in the central area of Xuancheng. This relationship weakened as the distance from the central area of the city increased. An increase in the frequency of travel of ride-hailing vehicles may reduce the occupancy rate of buses. Fifth, the average frequency of travel of ride-hailing vehicles was the highest on congested road sections, and they had the greatest impact on average speed of these sections, which indicates that ride-hailing has a significant impact on traffic congestion. These results show that it is important for the government to supervise ride-hailing vehicles through management measures and guide modes of public travel to reduce the negative impact of ride-hailing vehicles on traffic.

The results of this paper are based on data on the trajectories of vehicles in Xuancheng. However, Xuancheng is a medium-sized city in the context of China, and whether the results of this analysis are applicable to other cities in the country requires further examination. We need to use data on the trajectories of vehicles in larger as well as smaller cities to better understand the impact of ride-hailing vehicles on traffic. Of course, we need better methods of data collection and evaluation to better quantify the impact of ride-hailing vehicles on road network congestion. This can provide intuitive decision-making indicators for the government to supervise ride-hailing services, so that they can have a positive effect on the urban road network.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Zijun Liang conceived and designed the research and review; Wei Kong wrote the original draft and did formal analysis; Xuejuan Zhan revised the manuscript; Yun Xiao discussed the results. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

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