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Article

Is Ride-Hailing an Effective Tool for Improving Transportation Services in Suburban New Towns in China? Evidence from Wuhan Unicom Users' Mobile Phone Usage Big Data

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Abstract: Ride-hailing, a newly emerging mobility service that is popular worldwide, has become an efficient new mode of transportation. Nonetheless, the use and value of ride-hailing remain unclear for newly developed areas in the suburbs. We crawled through the usage data of 10 ride-hailing apps from Wuhan, China, and used Spatial Autocorrelation and Geographic Weighted Regression (GWR) to explore the role of ride-hailing in suburban new towns. We found that: (1) There is variability between urban and suburban in the use of ride-hailing, and residents in suburban new towns are more inclined to complete travel activities by ride-hailing. (2) In suburban new towns, ride-hailing has a complementary effect on public transportation, and this complementary role has differences in regional and demographic attributes. This effect is greater for high-tech industrial areas and is more in women and young people than in men and elderly people. Overall, this study confirms from a geospatial perspective that residents of suburban new towns are more likely to use ride-hailing compared to central urban areas and that ride-hailing can supplement the lack of public transportation services (PTS) in suburban areas and improve transportation services in such new towns where development and construction are not yet complete. Therefore, the integration of online taxis with traditional public transportation is expected to promote multi-modal transportation options in newly developed areas and help realize the development of suburban new towns. In addition, the study also found the effectiveness of using big data from mobile phones in studying residents' temporal and spatial behavior.

Keywords: mobile apps usage big data; ride-hailing; suburbanization; public transportation services; spatial regression analysis

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1. Introduction

Transportation is an important driving force for urban development, but the transportation construction of new suburban towns in China, especially public transportation, is still incomplete and hinders the development of new towns. Public transportation has become an important means of transportation for metropolitan residents to travel and connect spatially, which greatly promotes urban cluster connection, land use, and functional layout [1,2]. Although the construction of suburban new towns in China has been on the ascendant since the reform and opening up [3], the sparsely populated suburban new towns and low intensity of population activity [4] result in poorly connected transportation networks. Meanwhile, the construction and operation costs of conventional bus and rail infrastructure are too high [5], making suburban public transportation facilities insufficient and public transportation services(PTS) poor, generating problems such as long travel times, increased transportation costs, and inconvenience for commuters [6,7]. Therefore, to enhance suburban development, there is an urgent need to find a new way to complement the lack of PTS and improve urban transport services.

The emergence of ride-hailing may provide a new solution to the limited development of suburban new towns in China due to insufficient PTS. Information technology has enabled smartphones to connect drivers and passengers, giving rise to emerging mobile services. Ride-hailing refers to booking a car service through the Internet. Users use smartphones and GPS-enabled applications to issue demand instructions, and the service company passes the instructions to nearby suitable vehicles, which arrive at the designated location to pick up and drop off passengers. Its appearance has changed the travel behavior of citizens, especially after the outbreak of COVID-19, and public transportation is greatly affected by it [8]. The usage frequency of emerging mobile services led by ride-hailing has increased. In Toronto, ride-hailing has become the second most popular transportation alternative for residents without private cars [9]. In China, the ride-hailing appointment is not a specific type of travel vehicle but includes multiple modes such as private car, express car, carpool, and free ride. With the rapid development of mobile services, taxis in China have also achieved the function of online reservation, which can be directly called through App services, becoming another ride-hailing appointment travel mode. Therefore, the ride-hailing mentioned in this article refers to the travel service completed using the ride-hailing apps, which includes the above modes of special car, express car, carpool, and taxi services engaged in online booking.

Ride-hailing compensates for the inequality in service space caused by unequal taxi services, the unreasonable layout of public transportation facilities, and inadequate configuration [10,11], which bring conditions for improving suburban transport services and promoting the development of suburban new towns. Studies confirm that ride-hailing has both substitute [12–14] and complementary effect on public transport [15], studies also have shown that complementary effects occur more often in suburbs with less public transportation coverage [16]. Nevertheless, can ride-hailing be a valuable tool to compensate for the lack of PTS and improve transportation services in newly developed areas such as suburban new towns? Answering this question can help assist in policy formulation and urban planning for urban PTS in newly developed areas in suburban areas. This study attempts to answer this question in three ways. First, what are the spatially distinctive characteristics of the use of ride-hailing in the central city and suburban new towns? Second, what are the preferences of residents of different genders and ages in the new towns for ride-hailing? Third, what is the relationship between ride-hailing and public transportation in suburban new towns?

Using new data (China Unicom Mobile phone usage big data) which correlates the usage data of ride-hailing apps to the user's residence, we analyze the difference o in spatial distribution and population differences between urban and suburban ride-hailing apps in terms of the number of users and the duration of usage through mathematical statistics and spatial autocorrelation methods. Exploring the relationship between ride-hailing and public transportation in suburban new towns under different regions and population attributes by GWR to reveal the contribution of ride-hailing to the development of suburban new towns.

In addition, a new quantitative measurement method for studying the usage and distribution of ride-hailing is proposed. Mobile phone usage big data not only includes the user's social attributes (gender, age), app usage time, and usage status but also reflects the user's physical spatial location. Such data can be applied to more studies in the future, such as the visitation and psychological state of users using tourism apps.

The second part of the article reviews the impacts brought about by ride-hailing and their relationship with PTS and suburban new towns. Section 3 introduces the data and methods used, followed by the analysis of the results. Lastly, we summarize the conclusions, propose some policy implications, and point out the shortcomings of the study.

2. Literature Review

This study examines the impact of ride-hailing on suburban new towns in China, which are still incomplete in terms of urban services and suffer from a spatial mismatch between PTS and travel activities due to the effects of construction timing and market scale effects. Public transportation has become an essential mode of travel due to its high passenger capacity, cheapness, and low environmental pollution, and is crucial for developing suburban new towns. Therefore, to enhance transportation services for the development of new suburban towns, more attention needs to be paid to public transportation.

Since the suburbanization process in China is different from that in Europe and the United States, the demand for PTS caused by this also differs. Early on, suburbanization in China was shaped by the rapid urbanization development and land market reforms that started the spreading of urban boundaries to the suburbs [17,18]. As a transitional form, early suburbanization in China gave less consideration to quality of life and other urban service facilities, but the continued expansion of development to the suburbs led to a rapid increase in suburban travel behavior, and the contradiction between PTS and travel demand began to emerge. Meanwhile, suburbanization in Europe and the United States is an active migration of the middle class to the suburbs influenced by the emergence of the private automobile [19,20]. Therefore, Chinese suburban residents who lack private cars are not guaranteed daily travel and are highly dependent on PTS, while European and American residents can rely on a large number of private cars for their travel activities, resulting in low demand for PTS. Residents faced travel issues like insufficient PTS and hindered travel activities in the early stage of Chinese suburbanization.

To control the disorderly diffusion of urban boundaries and improve the quality of residents' lives, the Chinese government proposes to develop suburban new towns [21,22]. Unlike traditional satellite cities, suburban new towns are relatively independent cities with high industrialization and diversified urban functions [23]. Currently, with the advantages of vast land and low housing prices, China's suburban new towns have undertaken industrial and population transfer in some central urban areas, forming multiple employment and residential sub-centers [24]. Although the suburban new towns include transportation services as a key consideration during development and construction, the PTS support facilities in the new towns are not yet complete due to the problems of land fragmentation and low density of human activities, which are influenced by the construction timing and market scale effect [5], resulting in a poorly connected transportation network, low density of transportation stations, large service radius, and incomplete public transportation connections. The spatial mismatch of services leads to a surge in travel demand that still overwhelms roads and public transportation [25], resulting in inefficient and inconvenient transportation in suburban new towns. The outdated PTS can hardly meet the travel demand of suburban residents, which in turn leads to low industrial and population attractiveness of suburban new towns [26], forming a vicious circle and further inhibiting the growth of new towns.

The different stages of China's suburbanization development have been affected by the limitations brought by inadequate PTS, and the emergence of ride-hailing has created good travel conditions for suburban areas with low public transportation coverage rates and insufficient travel service capacity. A study of the factors influencing the demand for ride-hailing found that remote areas have low population density and low density of transportation facilities, but higher demand for ride-hailing [27]. Recent research has shown that ride-hailing can provide occasional trips that cannot be completed by walking or public transportation for people living outside the services of transportation hubs or bus stops [28], or cooperate with public transportation to become a part of multi-modal transport services in urban peripheral areas [29]. Brown pointed out that people in urban suburbs, rural areas, and even low-income communities use ride-hailing services more frequently than others under the same conditions [10]. Research in Accra and Kumasi, Ghana showed that the main users of ride-hailing did not come from the urban side, but from suburban areas [30].

At the same time, many studies have shown that ride-hailing has an alternative or complementary effect to PTS, and the complementary effect is more obvious in suburban areas, which to some extent the dependence on PTS for travel demand and therefore improving the transportation environment. The changes in travel patterns caused by the popularity of ride-hailing in three regions in the southern United States (Phoenix, Arizona, Atlanta, Georgia, and Austin, Texas), pointing out that 15% of people use ride-hailing to replace private cars and taxis, and 10.8% of people often use it to substitute PTS [31]. A study pointed out that ride-hailing has reduced the use of buses by 6% of Americans and the demand for light rail by 3% [32]. The data [33] shows that for Mexican passengers traveling to airports or railway stations, ride-hailing is more like a supplement to PTS rather than a substitute. A study from Chengdu, China, showed that ride-hailing has a stronger substitute effect on PTS in urban centers, while in suburbs with poor public transportation coverage, the complementary effect is more evident [16]. Another study from Chengdu revealed that the complementary effect of ride-hailing on PTS is more reflected in commuting hours and midnight when the capability of PTS is limited [25]. Nevertheless, the preference for the use of ride-hailing in suburban new towns and how they relate to PTS remains unclear, and there is a lack of research on this particular urban space.

Most of the existing studies on the impact of ride-hailing and PTS confirm these relationships at the transportation level (passenger volume, travel characteristics, travel behavior choices, etc.), and lack sufficient evidence to discuss them directly from a geospatial context. For example, a survey by the American Public Transport Association shows that ride-hailing is more popular during periods of less public transportation operations (such as 8:00 p.m. to 4:00 a.m.) [34]. In a questionnaire survey, over 40% of users who own private cars but still walk or ride will switch to using ride-hailing appointments when they lack public transportation or have difficulty parking [11].

Furthermore, previous studies indicated that there were demographic differences in the choice of ride-hailing travel decisions. Lots of studies have shown that ride-hailing users are mostly young and urban people [35] which is also related to income and education level [32,36]. In a survey of Chilean ride-hailing users, among wealthier and younger travelers, ride-hailing usage was more frequent per month [37]. Other studies have suggested that gender is also a factor affecting the use of ride-hailing services. Ref. [28] pointed out that men are more likely to use this than women. However, it is not known about the influence of demographic attributes such as gender, age, income, and education in the preference at the urban-suburban spatial level, and in the relationship between ride-hailing and public transportation.

Given China's unique urban form, there is limited understanding of the impact of ride-hailing on the new development areas of suburban new towns. This study attempts to fill this research gap by comparing newly developed areas with central urban areas to understand the spatial differences in the use of ride-hailing from a geospatial perspective, and further explore the relationship between ride-hailing services and PTS in suburban new towns with different regional and demographic attributes, to confirm whether ride-hailing can be an effective tool to make up for the lack of PTS and improve transportation services in suburban new towns. The results of the study can provide lessons for other regions that are undergoing similar urbanization processes in China so that appropriate planning and management policies can be developed.

3. Data and Methods

3.1. Study Area

The Wuhan Urban Development Zone (Figure 1) is selected as the research area, with a total area of 3271.5 km^2. According to the Wuhan Urban Master Plan (2010–2020), the urban spatial structure of 1 main city (central city), 3 sub-cities, and 3 new city groups have been formed in the central and suburban areas of Wuhan, the growth of suburban new towns has a certain foundation.

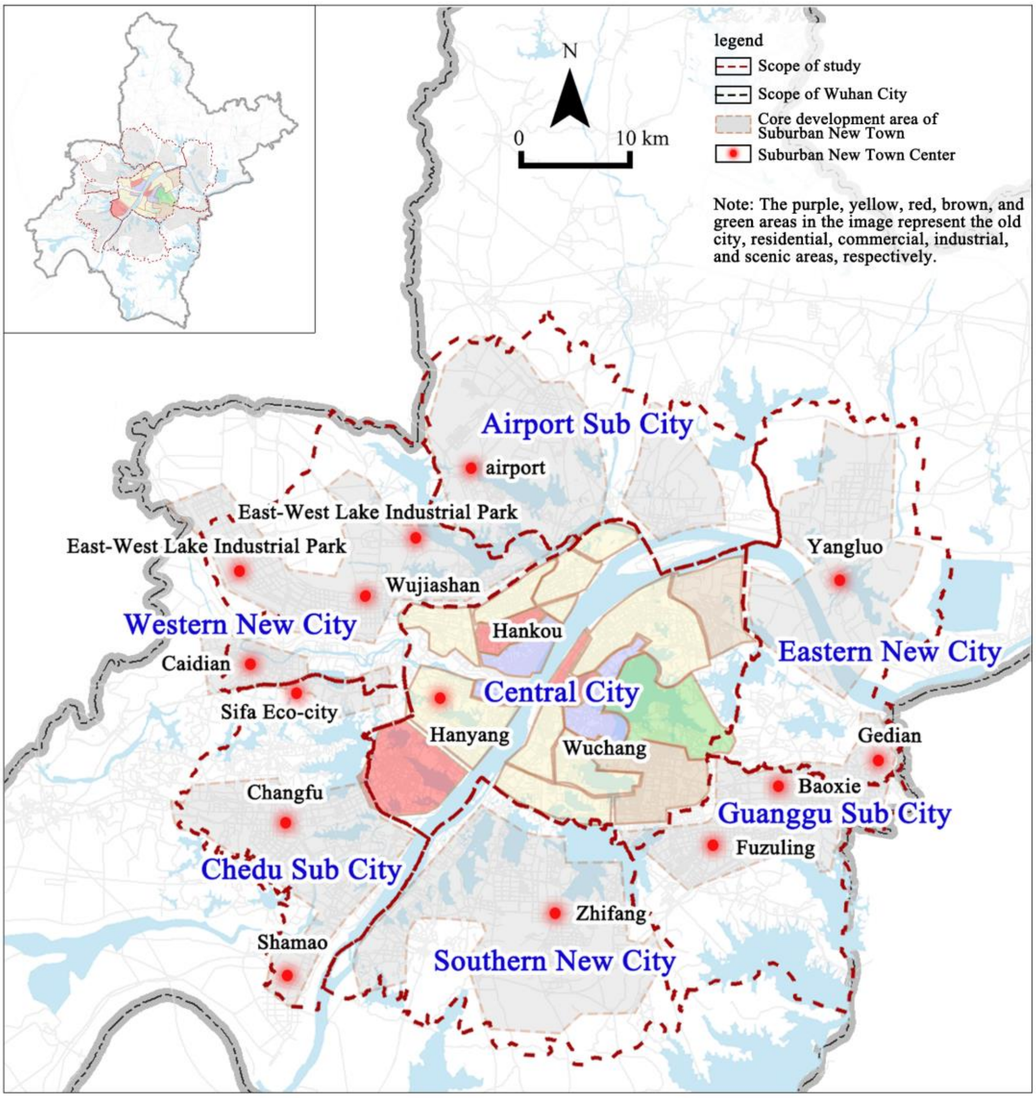

Figure 1. Schematic diagram of the research scope.

As a supercity in central China and the capital city of Hubei Province, Wuhan ranked ninth in China with a total GDP of 1562.295 billion yuan in 2021. By 2021, Wuhan has more than 400 bus routes, 14 subway-planned routes, and 11 implemented routes. The strong PTS has laid a solid foundation for urban enlargement. However, Wuhan's PTS also has the same problems as other cities in China, namely the PTS is perfect in the central urban areas while poor in the suburban areas due to the early construction of urban centers in China, the concentration of the population, and the long evolution sequence. However, the construction of suburban new towns is gradually underway, with a small population and the traditional location theory of service facilities, resulting in the inability of PTS in suburban new towns to provide good services.

The research area is the main urban function cluster area of Wuhan. The rail transit and key broadening industries that have been built in Wuhan are in it. In addition, the information infrastructure in the research area is complete, making spatial data more abundant and accurate, which strongly supports the observation of ride-hailing travel activities. Given that Wuhan is a typical Chinese city that has actively promoted the construction of suburban new towns in the past decade, the suburban new town area of Wuhan can be a valuable case for studying the contribution of ride-hailing to urban development in the context of information technology.

3.2. Research Data

3.2.1. Mobile Phone Usage Big Data

The current research data on ride-hailing comes largely from private companies or direct surveys of passengers. Data from private companies are affected by the operating status of different companies, which greatly hinders people from fully understanding the distribution of ride-hailing activities [10], and is not directly related to passengers' living and work environment (Personal daily behavior is mostly related to the environment and service facilities around their residence and construction site). Moreover, the data from passengers themselves are affected by the difficulty of data acquisition, resulting in a small amount of data and a significant impact from personal subjective consciousness.

Research data purchased from China Unicom Smart Steps Digital Technology Co. Ltd. (China Unicom is one of China's most important telecommunications companies, with a large market share in Wuhan. http://www.smartsteps.com/ (accessed on 4 October 2022)), which contains personally identifiable information, location of residence and work, as well as information on the time and traffic used when using all mobile apps. These data have been used in research on the evolution trend of mobile offices in China [38]. Among them, three datasets are used by us, and each data can be interconnected by a unique user number. (1) Usage data of ride-hailing apps, including the number of users and usage duration. We used data from 1 June to 30 June 2021 for each user using 10 popular mobile ride-hailing apps such as DiDi, T3 Chuxing, CaoCao Chuxing, etc. (enriching previous studies that used data from only one company). Although Wuhan was still in the COVID-19 epidemic in 2021, the epidemic situation in Wuhan was controlled in June and residents' travel activities resumed, so the data for that month was less affected by the epidemic factors. (2) Information about the coordinates of the user's residence. According to the platform code, the location where a user is considered to have the longest stay time from 9 p.m. to 8 a.m. is indicated as the user's residential location. The number of people living in each place can be obtained by aggregating the data of users' places of residence. (3) Information about the user's attributes, including gender and age.

The statistics of the number of ride-hailing users obtained by apps' names are shown in Table 1. Due to the existence of multiple apps used by one user, we conducted the same user identification work before conducting the analysis and eliminated the invalid usage duration data of each App when using (invalid usage duration refers to the time data during which a user uses a mobile App without generating data traffic, as well as data with a total usage duration of less than 1000 s for that month), which will result in a small number of users. Finally, a total of 114,965 valid users who frequently use ride-hailing apps were counted. Since the data of ride-hailing users are only Unicom users, the residential population data used for analysis also uses user data obtained from China Unicom to eliminate the bias caused by sampling. The obtained residential population data of Unicom users in each area are shown in Figure 2.

Table 1. Statistical Table of Wuhan Ride-hailing Apps Users from 1 June to 30 June 2021.

Name of Ride-Hailing Apps	Release Date	Number of App Users Recorded by the Platform (Person)
DiDi Chuxing	2012.9	1,117,432
T3 Chuxing	2019.7	165,349
Huaxiaozhu	2020.3	34,127
CaoCao Chuxing	2015.11	22,499
CaoCao Private car	2015.11	17,867
Wanshun Calling	2017.3	17,727
Shouyue	2015.9	5924
Shenzhou Private car	2015.1	4518
Xiangdao Chuxing	2018.11	940
RuQi Chuxing	2019.6	435

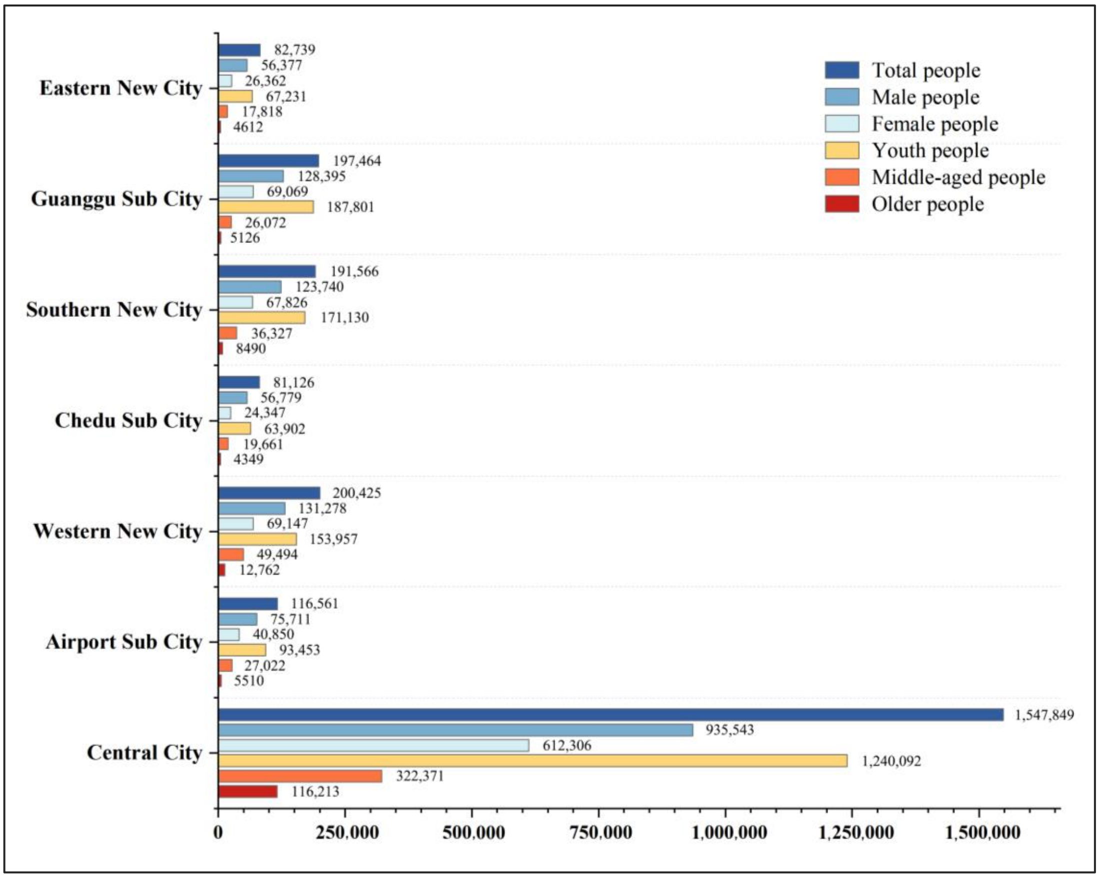

Figure 2. Population statistics of Unicom users living in each area.

3.2.2. Research Unit

Unlike the analysis that typically takes communities as the research unit, we use grids as the research unit, eliminating the impact of community differences on the one hand, and supplementing smaller-scale research on the other. Excluding the water area and wetland space, and combining the volume of actual sample data, the grid size of the studied urban space was determined to be 500 × 500 m, with a total of 13,524 grids. The sample data were spatially matched using Arc GIS spatial analysis and SQL statements. Since most of the effective usage data for users using ride-hailing apps are instantaneous and discontinuous, the duration data are counted monthly to enhance the reliability of the analysis results.

The changes in quantity and duration directly reflect the spatial heterogeneity characteristics of ride-hailing usage in Wuhan. Two indicators are used for statistics, one is the ratio of the number of people using ride-hailing apps within the grid to the total number of people living in the grid (Proportion of users), and the other is the average usage time of the total number of people using ride-hailing apps within the grid (Per capita usage time), which measures the ride-hailing usage in the central area and suburban new towns of Wuhan. We divided the research objects into five situations of the overall situation (regardless of gender and age), male and female, youth and middle-aged and older people to conduct a comparative study between the central city and suburban new town, to discover spatial differences and population preferences in the use of ride-hailing and further argue for the differential impact of the relationship between ride-hailing and PTS. Based on the classification of age groups by the WHO and the data recorded by China Unicom, we divided the age group between 18 and 44 years old into young people and the age group above 44 years old into middle-aged and elderly people. Since elderly people rarely use mobile phones, we conducted a combined analysis with middle-aged people.

3.2.3. Measurement of Public Transportation Services Level (PTSL)

To investigate whether ride-hailing can complement PTS and improve transportation services, it is necessary to measure the PTSL in Wuhan. Considering the transfer behavior of residents when they choose to take public transport in reality, we adopt the traffic reachability based on the minimum impedance as the PTSL indicator in Wuhan. The method uses the average minimum impedance from the center point to all destination locations as the accessibility evaluation index for the center point, which is used to evaluate the convenience of roads and transportation. Formulated as

$$A_i = \frac{1}{n-1}\sum_{\substack{j=1 \\ j \neq i}}^{n} (d_{ij}) \quad (1)$$

where A_i represents the accessibility of node i on the network; d_{ij} represents the minimum impedance between nodes i and j, which is expressed in time cost in this work. The accessibility of node i is the average of the minimum impedance of the node to all other nodes on the network (Figure 3). The disadvantage of this method is that it treats all destinations equally and does not take into account differences in travel purposes. However, our work is only aimed at measuring traffic convenience and does not consider travel purposes, so this method is applicable.

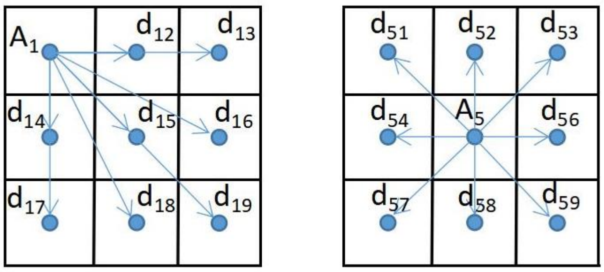

Figure 3. Illustration of accessibility evaluation based on minimum impedance.

First, we crawled the bus and subway stations and routes of Wuhan City in 2021 (excluding the unbuilt and not yet in operation data, as shown in Figure 4a,b) in AMap (A provider of navigation and location services solutions in China (https://lbs.amap.com/, accessed on 11 November 2022)), then we built Wuhan City public transportation network by traffic network analysis of Arc GIS, and we constructed Wuhan PTSL with the average minimum time used by the center point of the previously described 500-m grid through the traffic network to the center points of all other grids in the research scope. Finally, the evaluation map of the PTSL in Wuhan is obtained through spatial interpolation. The longer average minimum time indicates the lower PTSL in the area, as shown in Figure 4c, which shows that the further the distance from the central city, the longer the time taken from the grid center to the center of the rest of the grid, and the worse the service level, which means that the PTSL in Wuhan City shows a decreasing trend from the central city to the suburbs as a whole.

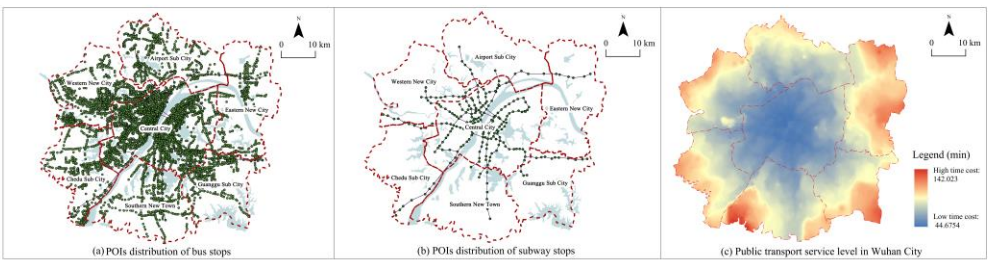

Figure 4. Public transportation in Wuhan City.

3.3. Research Methods

3.3.1. Spatial Autocorrelation

We use the Global Moran's I (GMI) and the Local Moran's I(LMI) to determine the spatial distribution of ride-hailing usage in the study area.

The GMI index is used to describe the overall distribution of a phenomenon, with the formula:

$$(Z) = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \tag{2}$$

In Formula (2), n is the total number of unit spaces within the study range, X_i and X_j is the proportion of people using the ride-hailing apps at the i-th and j-th spatial location, $\overline{X}$ is the average value of the proportion of users for all spatial units, and W_{ij} is the spatial neighbor weight of each spatial unit i and unit j within the study range, using inverse distance calculation, and the distance is the Euclidean distance between grid points. The GMI value (Z) is between $[-1, 1]$, greater than 0 indicates spatial agglomeration, and less than 0 indicates spatial dispersion. The larger the value, the greater the correlation of the spatial distribution. When the value approaches 0, it indicates that the spatial distribution is in a random state.

The LMI is used to reflect the high or low-value local spatial agglomeration of a phenomenon, calculated using the local analysis method LISA (Local Indications of Spatial Association). For the i-th regional cell, the formula for the LMI is:

$$Z(I_i) = \frac{\left(X_i - \overline{X}\right)}{S^2}\sum_j W_{ij}\left(X_j - \overline{X}\right) \tag{3}$$

In Formula (3)

$$S^2 = \frac{1}{n}\sum_i\left(X_i - \overline{X}\right)^2 \tag{4}$$

A positive value indicates that there are spatial clusters with high or low similarity values around the units in the study area, while a negative value indicates no similar spatial clusters. The result is divided into four aggregation types: H-H (High to High), L-L (Low to Low), H-L (High to Low), and L-H (Low to High).

3.3.2. Geographically Weighted Regression

GWR is used to explain the causes of geographical events with spatial heterogeneity. Compared to global regression models, it has a higher fitting effect on changes in spatial factors. formulated as

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{5}$$

In Formula (6), (u_i, v_i) is the geographic center coordinate of unit i, and $i = 1, 2, \ldots$, n, $\beta_k(u_i, v_i)$ is the k-th regression parameter of the continuous function in the i-th space, and ε_i is the random error of the i-th point.

A 500 m $\times$ 500 m spatial grid unit is adopted, with the proportion of users within the grid as the dependent variable and the PTSL as the independent variable. At the same time, considering that the demand for ride-hailing will also be influenced by road density [39,40] and POIs [41,42], we include them as control variables in the model. Road density is expressed by the per capita road length in the grid (Figure 5a), and business facility POIs are expressed by the per capita number of four types of facility points: shopping, dining, rest and recreation, and living services in the grid (Figure 5b).

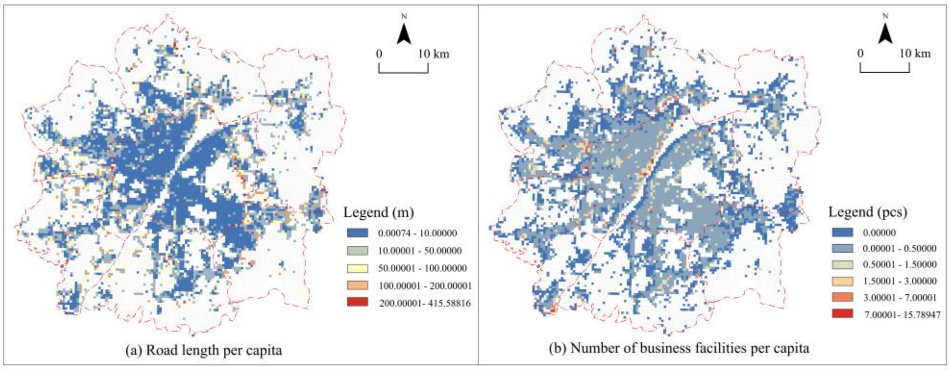

Figure 5. Plot of control variable results.

Classifying the model into the five aforementioned scenarios. The kernel function type is determined as the Gauss function, and the adaptive bandwidth is 20. Separate regression models are developed, which in turn explore the relationship between ride-hailing and PTS, and demonstrate whether there are regional and demographic attribute differences in this relationship.

4. Results

4.1. Spatial Distribution Characteristics of Ride-Hailing

4.1.1. Spatial Difference in the Number and Duration of Ride-Hailing Users

Figure 6 shows the distribution of the proportion of users using ride-hailing apps in urban and suburban areas, as well as statistical descriptive data for different genders and ages. As can be seen, in terms of the overall situation, the average proportion of users in suburban areas is 0.046, which is higher than that in central urban areas. From the perspective of spatial distribution, the proportion of users in suburban areas is higher than that in the central city, which means that the frequency of use is higher than that in central urban areas, and the areas that are farther away from the central city and closer to the suburban new towns are more likely to have high-value areas, especially in the Guanggu Sub-City. In terms of usage duration, the average per capita usage time in the central city is higher than that in the suburbs which may be due to the longer one-way usage time of ride-hailing users in the central city.

From the gender perspective, the total number of male users is higher than that of female users, and male users are more widely distributed, characterized by urban agglomeration and suburban dispersion. The data distribution of male users is consistent with the overall situation. Compared to men, women's range of ride-hailing use is more limited. From the perspective of spatial distribution, urban areas are more distributed than suburban areas, but areas with a high proportion of users still appear in the suburbs. However, this ratio is relatively low compared to males, which may be due to a large number of passengers believing that ride-hailing has a lower sense of safety than public transportation and taxis [43], while women have more concerns about safety [44] so that the number is relatively small. The average per capita usage time of females in urban areas is greater than that in suburbs, but the high-value areas are still more in suburbs than in urban areas, which may be caused by the relatively long travel distance in suburbs.

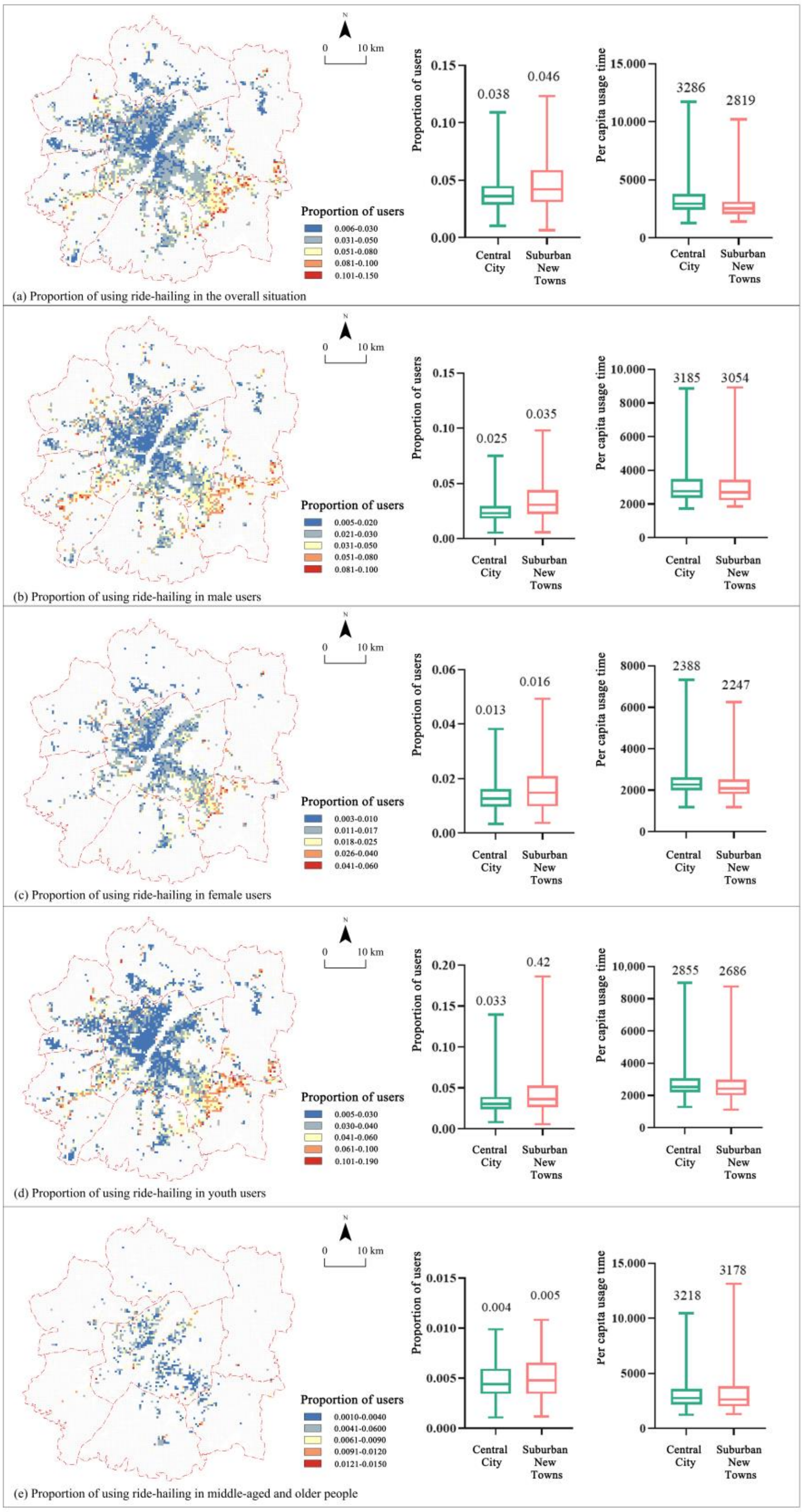

Figure 6. Distribution and statistical chart of ride-hailing usage.

From the age perspective, there are far more youth users than middle-aged and elderly people, covering the main areas of central urban areas and suburban new towns. The data results of young users are also consistent with the results of the overall situation and male users. The use of ride-hailing by middle-aged and elderly people is mostly limited to central urban areas, but there are also sporadic uses in suburbs. This may be due to the digital divide [45,46], the unfamiliarity of smartphone use, the difficulty of learning ride-hailing software, and the slow acceptance of ride-hailing. Moreover, the results indicate that in suburbs, even older people need to rely on ride-hailing to complete their travel. The distribution of per capita usage time for middle-aged and elderly people is opposite to that of young people, with the average and high-value areas showing a higher situation in the central city than in suburban areas. This may be because middle-aged and elderly people in urban areas are more likely to learn how to use smartphones than elderly people in suburban areas.

4.1.2. The Spatial Agglomeration Characteristics of Ride-Hailing Usage

Table 2 shows the GMI for the proportion of users in five situations. The GMI is greater than 0, and the Z-Score is greater than 2.58. The corresponding p values all pass the significance level test of 0.01, indicating that there is a positive correlation and significant spatial clustering characteristics in the proportion of users under different circumstances.

Table 2. The GMI results of ride-hailing usage.

Variable Name	Moran's I	Z-Score	Value p
in the overall situation	0.269929	112.215563	***
in male users	0.299457	91.932719	***
in female users	0.192515	67.568236	***
in youth users	0.310721	130.811306	***
in middle-aged and older people	0.019787	8.033488	***

*** indicates that $p < 0.001$.

Figure 7 shows the LMI results for the five categories of cases. In terms of the overall situation, H-H indicates that the proportion of users in this spatial unit is relatively high, and the surrounding areas are also relatively high. This type of area is widely distributed in the suburbs of Wuhan City, with the Guanggu Sub-City and Chedu Sub-City being the most prominent. The southern part of the central city close to the Chedu Sub-City also has obvious characteristics, which may be because although the area belongs to the central city in terms of administrative division, from the current situation of transportation development in Wuhan, the area has been divided into suburban areas. In addition, the southern part of the Eastern New City near the Guanggu Sub-City also shows H-H clustering. L-L means that the proportion of users in this spatial unit is relatively low, and the surrounding area is also relatively low. This type of ride-hailing is mainly distributed in the central city, as well as in the Western New Town and Airport Sub-City. L-H scattered distribution at the edge of suburban new towns, with no obvious clustering trend, and the H-L are opposite, scattered in the urban fringe of the central city.

The LMI of ride-hailing usage with male and young users is similar to the overall situation. When the user is a female, H-H mainly occurs in the Guanggu Sub-City and the Western New City, while L-L occurs in the central city and the Airport Sub-City. Other suburban new towns are not significant due to insufficient data volume, and L-H and H-L are still scattered and not clustered. When users are middle-aged and elderly, they exhibit L-L levels in the core area of the central city and areas near the Guanggu Sub-City, with a small number of H-H in the Western New City, and the agglomeration of other suburban new towns is not significant.

The GMI shows that the use of ride-hailing in Wuhan has a spatial agglomeration and a nonrandom distribution. The LMI indicates that there are hot spots (H-H clusters) and cold spots (L-L clusters) in this cluster. Among them, hot spots are mainly distributed in suburban new towns and areas close to them, while cold spots cover a large area of the central city and areas close to it, indicating that compared to the central city, a large number of suburban new town residents prefer to use ride-hailing to complete travel activities.

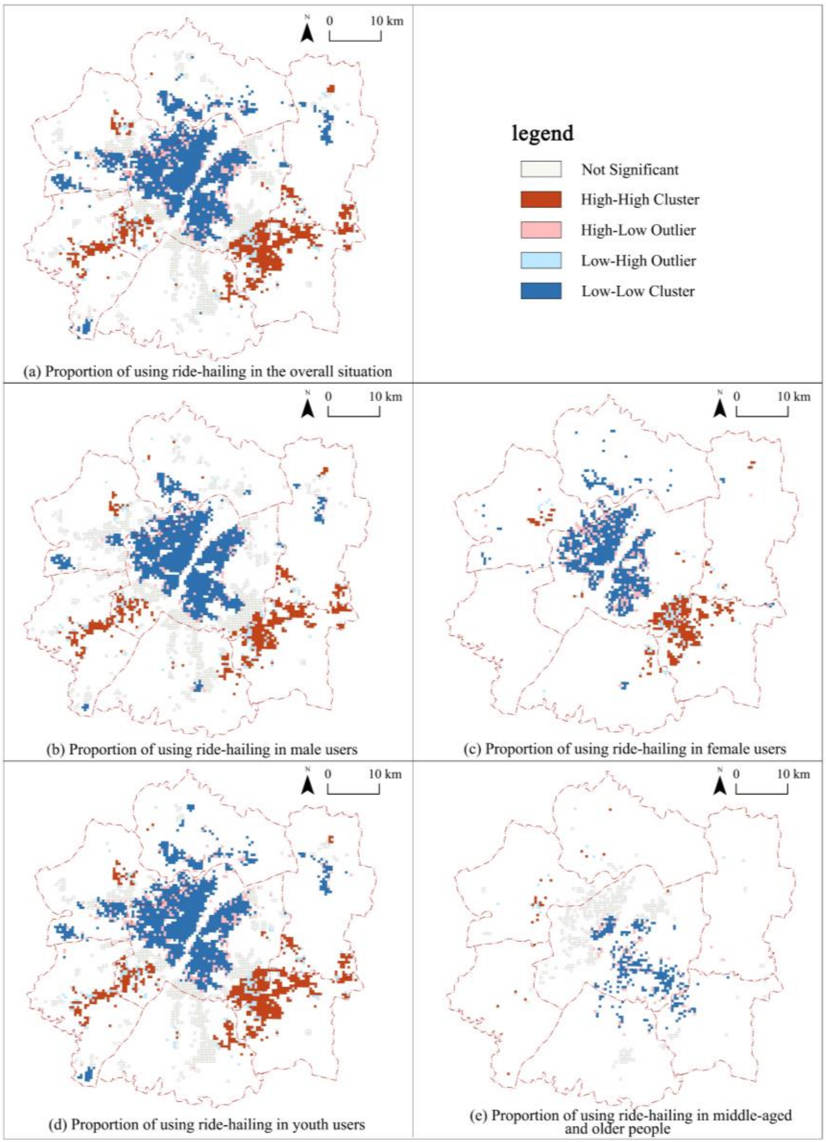

Figure 7. The LMI results of ride-hailing usage.

4.2. The Relationship between Ride-Hailing and PTS and Its Differences

As residents of suburban new towns prefer to use ride-hailing to complete their travel activities. We define the relationship between ride-hailing and public transportation in suburban new towns in a geospatial context: where PTS is lacking but ride-hailing users are more numerous, ride-hailing may complement public transportation because it provides an alternative in areas that are poor PTS. Conversely, where PTS is adequate, and there are more users of ride-hailing, it is likely to substitute public transportation.

Before experimenting, we used the Ordinary Least Squares (OLS) to test the relationship between independent and dependent variables. The regression results showed an average fit (except for the middle-aged and elderly cases), and all regression coefficients were significant only in the female case, while the business facilities per capita in other cases were insignificant and should be excluded, and there was no covariance between the variables. Meanwhile, the results of the spatial autocorrelation test of the residuals showed that they showed spatial clustering, indicating that the spatial autoregressive model should consider spatial heterogeneity. The significant cases of LM-Lag, LM-Error, Robust LM-test, and Robust LM-Error were determined based on the Lagrange Multiplier test results, for which different spatial models were selected for regression analysis. The overall, male, and youth chose the Spatial Durbin Model (SDM), while the female and middle-aged and elderly chose the Spatial Error Model (SEM). The regression coefficient of PTSL estimated from the global regression results is positive and passes the 1% significance test. Therefore, it is concluded that the PTSL and the use of ride-hailing show convergence and spatial dependence, which means that the lower the PTSL (the higher the time cost), the higher the number of ride-hailing use, indicating to some extent that ride-hailing has a complementary effect on public transportation. It shows that when PTS is insufficient, a new mode of transportation such as ride-hailing can compensate for this shortcoming and thus improve the transportation service in suburbs.

To explore the effects of spatially disparate differences, we further used GWR. The results of the three models are shown in Table 3. It can be seen that GWR results outperform the other models. Since GWR calculates a set of coefficient estimates for each grid cell, a map representation of the spatial distribution of the coefficient estimates of the variables within our study area is provided below.

4.2.1. Impact of Regional Differences

In the overall situation, the regression coefficient of PTSL is between −2.5 and 3.2, with both the average and median values being positive, and its impact is mainly positive. From the coefficient distribution results in Figure 8a, it can be seen that, in general, the impact of PTSL on the proportion of users is inconsistent between the suburban and central city, with mostly positive correlations in suburban areas and large differences in results in central urban areas. A positive correlation indicates that in suburban areas, the longer the time of using PTS, the higher the proportion of ride-hailing users, which means that the poorer the PTSL, the more residents tend to adopt ride-hailing for travel activities, and the ride-hailing complemented the PTS, thus improving transportation services in areas with poor PTS.

Based on the regression results for the overall situation, we find that the relationship between ride-hailing and PTS also shows inconsistency within each suburban new town. This positive effect is strong in the vicinity of the Fuzuling and Gedian areas in the Guanggu Sub-City, the Changfu area in the Chedu Sub-City, the East-West Lake Industrial Park in the Western New City, and the Airport area in the Airport Sub-City, indicating that there is a strong complementary relationship of ride-hailing to the PTS in these areas. On the other hand, the Baoxie area in the Guanggu Sub-City, the Shamao area in the Chedu Sub-City, the Wujiashan area in the Western New City, and the Yangluo area in the Eastern New City show a negative influence, and in these areas, the ride-hailing and PTS show a mutually constraining effect.

An analysis of the positively influenced areas shows that most of these areas are high-tech industrial parks and areas with concentrated university campuses. The Airport Sub-City serves as the air transportation center of Wuhan, the Changfu area is a large automobile manufacturing center for the whole of Wuhan and even China, and the Fuzuling and East-West Lake industrial parks serve as high-tech development zones in Wuhan and have many university campuses. The permanent residents of these areas are mostly young and highly educated and have a greater potential to choose to use ride-hailing. Therefore, when PTS is insufficient, people living in these areas are more likely to turn to using ride-hailing, and the complementary effect of ride-hailing on the PTS in these areas is more prominent. The areas with negative correlation are mainly developed by food processing, heavy chemical industry, textile industry, and large residential areas, where the residents are older and less likely to use such mobility services, and ride-hailing has less of a role in complementing PTS in such areas.

Table 3. Comparison of model results.

Models	Regression Coefficient			AICc	Sigma	R^2	R^2 Adjusted
	PTSL	Per Capita Road Length	Number of Commercial Facilities Per Capita				
OLS (The overall situation)	0.076 ***	0.003 ***	−0.006	−7578.59	0.071	0.21	0.21
OLS (Male users)	0.108 ***	0.003 ***	−0.007	−7061.06	0.067	0.29	0.29
OLS (Female users)	0.180 ***	0.009 ***	−0.038 ***	−2688.97	0.114	0.17	0.17
OLS (Youth users)	0.161 ***	0.004 ***	−0.006	−5277.31	0.098	0.25	0.24
OLS (Middle-aged and older people)	0.029 ***	0.010 ***	−0.009	−3280.33	0.026	0.63	0.63
SDM (The overall situation)	0.114 ***	0.002 ***	-	−8456.16	0.057	0.45	-
SDM (Male users)	0.106 ***	0.002 ***	-	−7462.63	0.059	0.43	-
SEM (Female users)	0.156 ***	0.008 ***	−0.038	−2997.11	0.100	0.32	-
SDM (Youth users)	0.140 ***	0.003 ***	-	−5756.00	0.085	0.42	-
SEM (Middle-aged and older people)	0.031 ***	0.207 ***	-	−3300.77	0.025	0.64	-
GWR (The overall situation)	0.057 *** (Average value)	0.002 *** (Average value)	-	−5459.99	0.053	0.74	0.57
GWR (Male users)	0.072 *** (Average value)	0.002 *** (Average value)	-	−5545.29	0.046	0.79	0.64
GWR (Female users)	0.090 *** (Average value)	0.005 *** (Average value)	0.039 *** (Average value)	−1789.12	0.089	0.71	0.43
GWR (Youth users)	0.102 *** (Average value)	0.003 *** (Average value)	-	−4003.97	0.071	0.70	0.49
GWR (Middle-aged and older people)	0.014 *** (Average value)	0.015 *** (Average value)	-	−2171.23	0.041	0.47	0.13

*** indicates that $p < 0.001$.

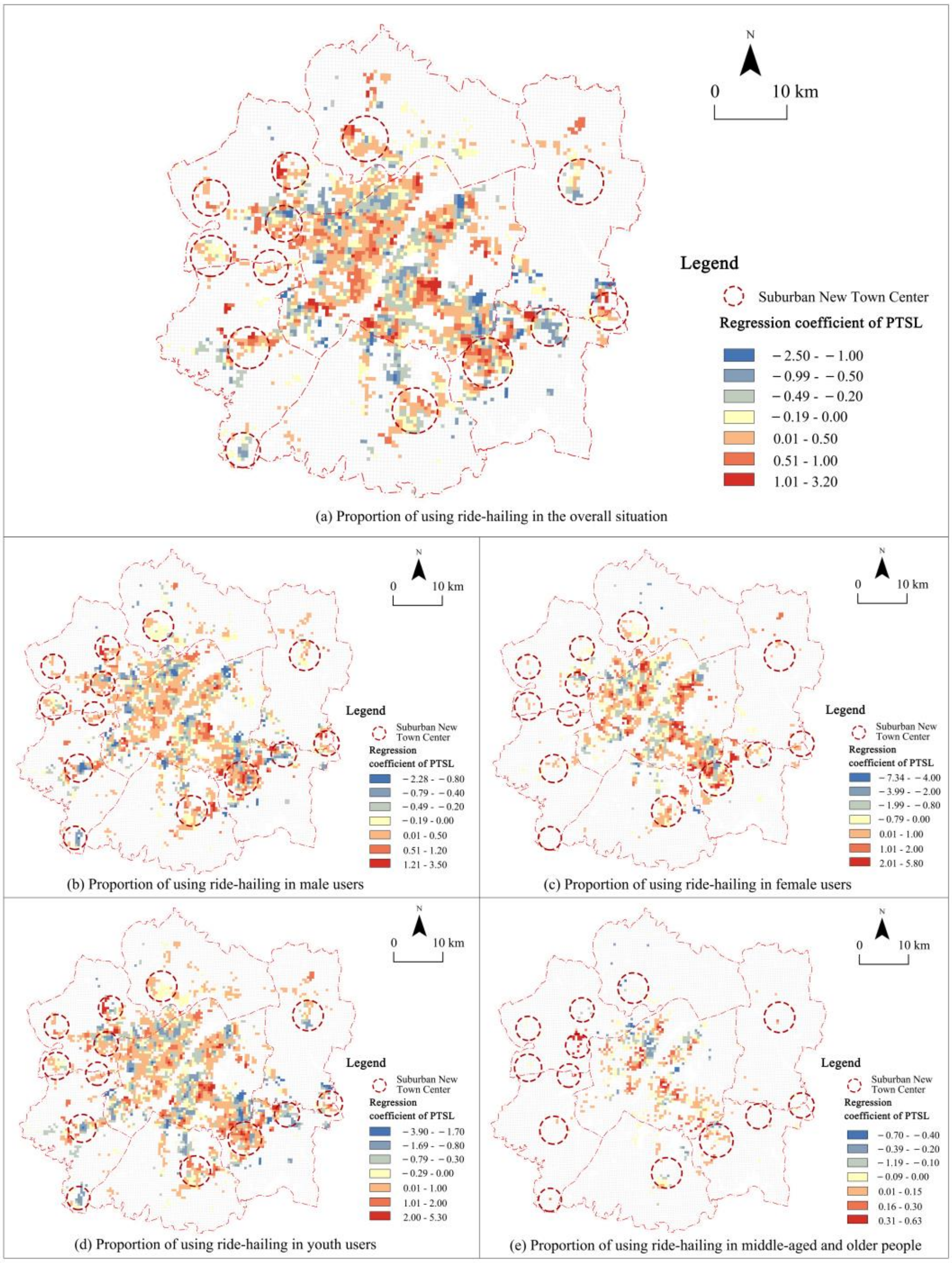

Figure 8. Variables and GWR regression results.

Furthermore, these explanations remain speculative, as this topic requires further research. In any case, this is an important finding that suggests regional differences in the complementary role of ride-hailing to PTS in suburban areas.

4.2.2. Impact of Population Attribute Differences

The regression results for male users are similar to the overall situation, showing a positive correlation in suburban new town centers and a small number of negative correlations in some areas, while the regression results for women show a largely positive correlation in suburban new towns. The regression coefficient of positive correlation for women is from 0 to 5.8, which is greater than that for men, which is from 0 to 3.5, indicating that the impact of ride-hailing on PTS is influenced by gender differences, with a higher impact on women than on men. This may be because women prefer to take public transportation [47]. When public transportation is lacking, the efficient service and privacy of ride-hailing may encourage women to choose to use it more, Men may have more choices, such as self-driving and cycling, with a lower tendency to choose ride-hailing than women.

The regression results of young users also show that the regression coefficients are mostly positively correlated in the suburban new town centers, with a small number of negatively correlated areas, similar to the overall results, where traditional industries are clustered with large, old residential areas. The GWR regression results for middle-aged and older people are worse than SEM, suggesting that for older adults, the complementary role of ride-hailing to PTS varies less spatially. In suburban new towns, the positive correlation regression coefficient values for youth users are much larger than those for middle-aged and older people, indicating that the complementary effect of ride-hailing on PTS is larger for youth than for middle-aged and elderly. This may also be due to a digital gap faced by the elderly. When there is a lack of public transportation, young people can quickly choose ride-hailing due to their mastery of technology, but middle-aged and elderly people are less likely to choose ride-hailing due to mobile phone usage issues.

5. Conclusions and Discussion

To explore whether ride-hailing can become an effective tool for improving urban transportation services when PTS is insufficient in suburban new towns, we use new data (mobile phone usage big data), by analyzing the spatial distribution characteristics of the proportion of users and per capita usage time of using ride-hailing apps in five situations, and found suburban heterogeneity in them. By quantitatively measuring the PTSL, and conducting regression analysis with the user data of ride-hailing apps, we further confirm the complementary role that ride-hailing can play in improving transport services when PTS in suburban new towns is inadequate, and suggest opportunities for the development of new towns:

- Compared to the central city, many areas in the suburbs have more users and longer usage periods of ride-hailing, and residents of suburban new towns used ride-hailing more than those in the central city. More males, females, and youths in suburban new towns use ride-hailing than in central urban areas, while more middle-aged and elderly people in central urban areas use ride-hailing than in suburban new towns.
- In terms of spatial distribution characteristics, the number of people using ride-hailing apps under different circumstances shows a small clustering characteristic distribution in suburban areas. The hot spots of clustering are mainly distributed in suburban new towns and areas close to new towns, while the cold spots are mostly distributed in central urban areas, indicating that residents in suburban new towns are more inclined to use ride-hailing to complete their travel activities.
- The regression results show that in suburban areas, higher public transportation time cost consumption is positively correlated with more use of ride-hailing, which means that residents in suburban areas with lower PTSL are more likely to use ride-hailing, and when PTS is lacking, ride-hailing plays a complementary role. There are regional differences in this complementary effect, which is more prominent in high-tech industrial areas and less pronounced in traditional industrial and old residential areas. It also has gender and age differences, with a greater effect on female users than male users, and a greater complementary effect on young users than middle-aged and older users.

This paper confirms from a geospatial perspective that residents of suburban new towns use more ride-hailing than those in the central city, and it also confirms that ride-hailing can make up for the lack of PTS in suburban new towns and improve the travel environment in suburban new towns, which can help provide services to cities with incomplete public service facilities and support efficient production and living activities in suburban new towns in China. In addition, we also find that there are regional and demographic attribute differences in this complementary role, thus assisting in planning transportation service systems in suburban towns. Additionally, we used a new type of research data. Mobile phone usage big data effectively observes and correlates individual virtual activities (online car-calling, online shopping, online dating, etc.) and physical activities (spatial presence, travel OD, travel chain, etc.). A new data method for studying human spatiotemporal behavior and urban activities in the information age is provided by this work.

Policymakers can benefit from this study. First, for new suburban cities where PTS is incomplete and travel costs are high, ride-hailing can be a new mode of public transportation that complements existing PTS. The cost of ride-hailing should be appropriately reduced, and ride-hailing should be encouraged to become part of multi-modal transport services in the suburbs, preferably developed and operated by public authorities [48]. Secondarily, the demand for ride-hailing varies across different types of suburban towns. This may be influenced by the type of industry in the area. In general, areas with high-tech industries have more young people and higher demand for ride-hailing. Therefore, the number of ride-hailing in this type of area can be increased and the comfort of the service can be improved. Moreover, the use of ride-hailing is influenced by demographic differences, and women and middle-aged and elderly people are more likely to become vulnerable. It is necessary to strengthen the right of women when using ride-hailing services and advocate the addition of female-specific ride-hailing services. At the same time, to enhance the ability of middle-aged and elderly people to use new technologies through information-based education, and eliminate the unfairness brought about by the digital divide is needed. Finally, although ride-hailing can be an effective tool for improving travel services in suburban new towns, relying on it blindly can lead to environmental damage, imbalance in the transportation market, and other issues. It is significant that limit the ride-hailing service periods and enhance the use of night or no bus operation time to create a good transportation service platform.

Despite the significance of our results, this study has several limitations which can pave the way for future research. Initially, due to the limitations of data acquisition channels, only one month of usage data was available for us, without establishing multiple time series and long-term research, which may have deviations in different time periods for fully understanding the impact of ride-hailing booking on public transportation. Second, although the measurement of PTSL in this article considers the transfer between the bus and the subway, it still lacks consideration of the actual service time and shift of them. If this part of the content is revised in subsequent research, it will enhance the scientific nature of this study. Last but not least, this paper fails to delve into the regional differences in the complementary relationship between ride-hailing and public transportation in suburban new towns, and subsequent studies can include factors such as regional housing prices, wage levels, and industrial distribution to explore the causes of such differences to improve the PTSL in suburban areas and promote the development of the region.

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References

1. Polzin, S.E. Transportation/Land-Use Relationship: Public Transit's Impact on Land Use. *J. Urban Plan. Dev.* **1999**, *125*, 135–151. [CrossRef]
2. Su, H.; Wu, J.H.; Tan, Y.; Bao, Y.; Song, B.; He, X. A land use and transportation integration method for land use allocation and transportation strategies in China. *Transp. Res. Part A Policy Pract.* **2014**, *69*, 329–353. [CrossRef]
3. Governa, F.; Sampieri, A. Urbanisation processes and new towns in contemporary China: A critical understanding from a decentred view. *Urban Stud.* **2020**, *57*, 366–382. [CrossRef]
4. Long Ying, W.k. Several Realistic Problems of China's Urbanization: Spatial Expansion, Population Shrinkage, Low Density Human Activity, and Urban Scope Definition. *Urban Plan. Forum* **2016**, *2*, 72–77. [CrossRef]
5. Krugman, P. Urban concentration: The role of increasing returns and transport costs. *Int. Reg. Sci. Rev.* **1996**, *19*, 5–30. [CrossRef]
6. Ahmed, Q.I.; Lu, H.; Ye, S. Urban transportation and equity: A case study of Beijing and Karachi. *Transp. Res. Part A Policy Pract.* **2008**, *42*, 125–139. [CrossRef]
7. Zhao, P. The determinants of the commuting burden of low-income workers: Evidence from Beijing. *Environ. Plan. A Econ. Space* **2015**, *47*, 1736–1755. [CrossRef]
8. Das, S.; Boruah, A.; Banerjee, A.; Raoniar, R.; Nama, S.; Maurya, A.K. Impact of COVID-19: A radical modal shift from public to private transport mode. *Transp. Policy* **2021**, *109*, 1–11. [CrossRef]
9. Mashrur, S.M.; Wang, K.; Habib, K.N. Will COVID-19 be the end for the public transit? Investigating the impacts of public health crisis on transit mode choice. *Transp. Res. Part A Policy Pract.* **2022**, *164*, 352–378. [CrossRef]
10. Brown, A. Redefining Car Access Ride-Hail Travel and Use in Los Angeles. *J. Am. Plan. Assoc.* **2019**, *85*, 83–95. [CrossRef]
11. Tang, B.J.; Li, X.Y.; Yu, B.Y.; Wei, Y.M. How app-based ride-hailing services influence travel behavior: An empirical study from China. *Int. J. Sustain. Transp.* **2020**, *14*, 554–568. [CrossRef]
12. Anderson, D.N. "Not just a taxi"? For-profit ridesharing, driver strategies, and VMT. *Transportation* **2014**, *41*, 1099–1117. [CrossRef]
13. Gloss, M.; McGregor, M.; Brown, B. Designing for Labour: Uber and the On-Demand Mobile Workforce. In Proceedings of the 34th Annual CHI Conference on Human Factors in Computing Systems (CHI4GOOD), San Jose, CA, USA, 7–12 May 2016; pp. 1632–1643.
14. Rayle, L.; Dai, D.; Chan, N.; Cervero, R.; Shaheen, S. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transp. Policy* **2016**, *45*, 168–178. [CrossRef]
15. Jin, S.T.; Kong, H.; Wu, R.; Sui, D.Z. Ridesourcing, the sharing economy, and the future of cities. *Cities* **2018**, *76*, 96–104. [CrossRef]
16. Kong, H.; Zhang, X.; Zhao, J. How does ridesourcing substitute for public transit? A geospatial perspective in Chengdu, China. *J. Transp. Geogr.* **2020**, *86*, 102769. [CrossRef]
17. Shen, J.; Wu, F.L. Moving to the suburbs: Demand-side driving forces of suburban growth in China. *Environ. Plan. A Econ. Space* **2013**, *45*, 1823–1844. [CrossRef]
18. Song, Y.; Chen, B.; Kwan, M.-P. How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities. *J. Clean. Prod.* **2020**, *246*, 119018. [CrossRef]
19. Wirth, L. Urbanism as a Way of Life. *Am. J. Sociol.* **1938**, *44*, 1–24. [CrossRef]
20. Mieszkowski, P.; Mills, E.S. The Causes of Metropolitan Suburbanization. *J. Econ. Perspect.* **1993**, *7*, 135–147. [CrossRef]
21. Long, Y. Urban Spatial Development, Quality and Vibrancy of New Areas. *Urban Plan. Int.* **2017**, *32*, 6–9. [CrossRef]
22. Zou, Y.; Zhao, W. Making a new area in Xiong'an: Incentives and challenges of China's "Millennium Plan". *Geoforum* **2018**, *88*, 45–48. [CrossRef]
23. Shen, J.; Wu, F.L. The Suburb as a Space of Capital Accumulation: The Development of New Towns in Shanghai, China. *Antipode* **2017**, *49*, 761–780. [CrossRef]
24. Li, Z.G.; Chen, Y.Y.; Wu, R. The assemblage and making of suburbs in post-reform China: The case of Guangzhou. *Urban Geogr.* **2020**, *41*, 990–1009. [CrossRef]
25. Qiao, S.; Yeh, A.G.O. Is ride-hailing a valuable means of transport in newly developed areas under TOD-oriented urbanization in China? Evidence from Chengdu City. *J. Transp. Geogr.* **2021**, *96*, 103183. [CrossRef]
26. Wu, W. Urban Amenity, Quality of Life and Urban Development. *Urban Plan. Forum* **2010**, *2010*, 71–75.
27. Yang, H.; Huo, J.; Pan, R.; Xie, K.; Zhang, W.; Luo, X. Exploring built environment factors that influence the market share of ridesourcing service. *Appl. Geogr.* **2022**, *142*, 102699. [CrossRef]
28. Sabogal-Cardona, O.; Oviedo, D.; Scholl, L.; Crotte, A.; Bedoya-Maya, F. Not my usual trip: Ride-hailing characterization in Mexico City. *Travel Behav. Soc.* **2021**, *25*, 233–245. [CrossRef]
29. Wright, S.; Nelson, J.D.; Cottrill, C.D. MaaS for the suburban market: Incorporating carpooling in the mix. *Transp. Res. Part A Policy Pract.* **2020**, *131*, 206–218. [CrossRef]
30. Acheampong, R.A.; Siiba, A.; Okyere, D.K.; Tuffour, J.P. Mobility-on-demand: An empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. *Transp. Res. Part C Emerg. Technol.* **2020**, *115*, 102638. [CrossRef]
31. Lee, Y.; Chen, G.Y.-H.; Circella, G.; Mokhtarian, P.L. Substitution or complementarity? A latent-class cluster analysis of ridehailing impacts on the use of other travel modes in three southern U.S. cities. *Transp. Res. Part D Transp. Environ.* **2022**, *104*, 103167. [CrossRef]

32. Clewlow, R.R.; Mishra, G.S. Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States. Institute of Transportation Studies, University of California, Davis, Research Report UCD-ITS-RR-17-0. 2017. Available online: https://escholarship.org/uc/item/82w2z91j (accessed on 20 January 2023).
33. Yandex. Carsharing in Moscow. Available online: https://yandex.ru/company/researches/2021/drive (accessed on 1 February 2023).
34. Murphy, C. Shared Mobility and the Transformation of Public Transit. Available online: https://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf (accessed on 1 February 2023).
35. Azimi, G.; Rahimi, A.; Jin, X. Exploring the attitudes of Millennials and Generation Xers toward ridesourcing services. *Transportation* **2022**, *49*, 1765–1799. [CrossRef]
36. Conway, M.W.; Salon, D.; King, D.A. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Sci.* **2018**, *2*, 79. [CrossRef]
37. Tirachini, A.; del Rio, M. Ride-hailing in Santiago de Chile: Users' characterization and effects on travel behavior. *Transp. Policy* **2019**, *82*, 46–57. [CrossRef]
38. Niu, Q.; Zhang, H.; Wu, L.; Zou, W. Urban-suburban heterogeneity of mobile office development in recent years: Based on mobile office app usage big data of China Unicom users in Wuhan in 2019 and 2021. *Prog. Geogr.* **2022**, *41*, 1428–1439. [CrossRef]
39. Wang, S.; Noland, R.B. Variation in ride-hailing trips in Chengdu, China. *Transp. Res. Part D Transp. Environ.* **2021**, *90*, 102596. [CrossRef]
40. Yu, H.; Peng, Z.-R. Exploring the spatial variation of ridesourcing demand and its relationship to build environment and socioeconomic factors with the geographically weighted Poisson regression. *J. Transp. Geogr.* **2019**, *75*, 147–163. [CrossRef]
41. Li, X.; Xu, J.; Du, M.; Liu, D.; Kwan, M.-P. Understanding the spatiotemporal variation of ride-hailing orders under different travel distances. *Travel Behav. Soc.* **2023**, *32*, 100581. [CrossRef]
42. Zheng, Z.; Zhang, J.; Zhang, L.; Li, M.; Rong, P.; Qin, Y. Understanding the impact of the built environment on ride-hailing from a spatio-temporal perspective: A fine-scale empirical study from China. *Cities* **2022**, *126*, 103706. [CrossRef]
43. Jing, P.; Chen, Y.; Wang, X.; Pan, K.; Yuan, D. Evaluating the effectiveness of Didi ride-hailing security measures: An integration model. *Transp. Res. Part F Traffic Psychol. Behav.* **2021**, *76*, 139–166. [CrossRef]
44. Liu, Y.; Gao, Q.; Rau, P.-L.P. Chinese passengers' security perceptions of ride-hailing services: An integrated approach combining general and situational perspectives. *Travel Behav. Soc.* **2022**, *26*, 250–269. [CrossRef]
45. Niehaves, B.; Plattfaut, R. Internet adoption by the elderly: Employing IS technology acceptance theories for understanding the age-related digital divide. *Eur. J. Inf. Syst.* **2014**, *23*, 708–726. [CrossRef]
46. Yang, J.H.; Du, P. Gender, capital endowment and digital exclusion of older people in China. *Ageing Soc.* **2021**, *41*, 2502–2526. [CrossRef]
47. Cheng, L.; Chen, X.W.; Yang, S.; Wu, J.X.; Yang, M. Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. *Transp. Lett.* **2019**, *11*, 341–349. [CrossRef]
48. Jittrapirom, P.; Marchau, V.; van der Heijden, R.; Meurs, H. Future implementation of mobility as a service (MaaS): Results of an international Delphi study. *Travel Behav. Soc.* **2020**, *21*, 281–294. [CrossRef]

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