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Revealing the Varying Impact of Urban Built Environment on Online Car-Hailing Travel in Spatio-Temporal Dimension: An Exploratory Analysis in Chengdu, China

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Abstract: Online car-hailing travel is an increasingly popular mode of urban transport. A fundamental understanding of the relationship between the urban built environment and online car-hailing travel is essential for developing the corresponding traffic strategy and addressing sustainable urban planning and design. However, the varying impact of the urban built environment on online car-hailing travel in the spatial dimension has not been sufficiently investigated. This paper aims to fill this gap by using geographically weighted regression (GWR) to check the spatial heterogeneity of the likely influence. The result shows that the GWR model is superior to the global model (OLS) from the perspective of goodness of fit. The study finds that the recreation and entertainment Point of Interest (POI) and the residential district POI are the most influential factors on night online car-hailing travel. Land-use mix is found to have a positive effect on online car-hailing travel, and online car-hailing services can be a complementary mode for public transport, especially in suburban areas.

Keywords: urban built environment; online car-hailing travel; geographical weighted regression; POI

1. Introduction

Online car-hailing travel is becoming an emerging and fast-growing mode of transportation in cities, because of its convenient booking service and flexible door-to-door service (e.g., Uber, Lyft, and Didi). The number of online car-hailing services in China is also growing rapidly. Statistics from China Internet Network Information Center 2018 show that, by the end of 2017, there had been 236 million users of Express and Private Car Service in China, which increased 40.6% from 2016. Online car-hailing travel is undeniably becoming a key component of urban mobility. However, when an emerging transportation mode grows rapidly, the urban planners and transport administrators also face some difficult challenges. Such challenges include how to guide and manage the development of online car-hailing, how to integrate it into the multiple transportation systems (e.g., car transit, bus transit, taxi transit, subway transit, and non-motorized traffic), and how to integrate built environment policies (e.g., regional development plans, land mixed-use development, and street network improvement) with transportation policies (e.g., online car-hailing services management and bus and taxi operation management). Although previous studies have attempted to explore travel patterns [1], accessibility [2], or carpooling algorithm [3] to provide a better on-demand ride service, to the best of the authors' knowledge, few efforts have been made to investigate the links between the built environment and online car-hailing travel. Understanding such relationships will be critical when developing traffic strategies or addressing urban planning and design [4–6]. Thus, this paper aims to fill this gap by examining the spatio-temporal relationships between online car-hailing travel and the built environment using a geographical weighted regression (GWR) model.

The structure of this paper is organized as follows. Section 2 reviews related research on relationships between travel behavior and the built environment. Section 3 describes the study area and data, including POI data and online car-hailing travel data. Section 4 uses the GWR model to fit the field data in detail. Section 5 presents and discusses the model results. Section 6 concludes the paper and notes the limitations.

2. Literature Review

Over the last several decades, a great number of studies have demonstrated that the built environment has a sustained impact on travel behavior [5,7,8]. Numerous scholars have measured these relationships; for instance, it has been found that an increase in the degree of land-use mix can reduce the vehicle miles traveled (VMT) [7]; less distance to CBD results in more VMT per day [9]; and the job-housing balance, block size, intersection density, distance to store, or nearest park have an influence on trips taken on foot [10]. Cervero and Kockelman (1997) factorized built environment attributes into three D-variables (density, diversity, and design); Ewing and Cervero (2001, 2010) then extended this into seven D-variables (e.g., density, diversity, design, destination accessibility, distance to transit, demand management, and demographics) [11,12]. They drew several generalizable conclusions utilizing a meta-analysis method. The first one is that VMT is the most relevant to accessibility to destination. Second, trips on foot are mostly affected by land-use mix and intersection density. The last conclusion is that bus trips are mostly affected by the distance to transit and the street network design. The above studies contribute to understanding of the links between the built environment and travel, however, there are still several issues in the previous studies.

Firstly, the travel behavior data in these studies mostly come from travel surveys. Although travel survey data has made a tremendous contribution to previous research, there is no denying that conducting traditional travel surveys is time-consuming, energy-consuming, error-prone, and not very cost-effective, and additionally, most data is cross-sectional [13]. Therefore, the research process of travel behavior faces a data-hungry but data-poor dilemma. Recently, the widespread application of information and communication technology has provided an unprecedented chance to track trillions of digital footprints (e.g., smartcard data, mobile phone data, GPS trajectory data, and order data), which can further promote travel behavior research. Yang et al. (2018) investigated the main land use factors that impact taxi demand by using GPS trajectory data, and they found a positive correction between accessibility to subways and taxi ridership [14]. Ge et al. (2017) analyzed the relationship between taxi ridership and built environment, and they discovered that health care area is the most critical factor in all land use variables [15]. However, the influence of the built environment on online car-hailing travel has received relatively little attention, which may limit the management and development of online car-hailing services.

Secondly, the acquisition of built environment data is another issue, because the data is hard to come by. For example, Cervero and Kockelman (1997) collected density data, design data, and diversity data from several different sources; Ding et al. (2017) obtained built environment data from five channels [16]; and Zegras (2007), Munshine (2016, 2013), and other scholars obtained various data from multiple departments [17–19]. The plight of data acquisition hinders built environment/travel studies. In addition, the analysis unit is very important [20]. In existent research, the dominant analysis unit is the traditional traffic analysis zone (TAZ) [5,9,21], whereby divisions are mainly based on the following factors: natural boundaries (e.g., rails and rivers), administrative division, census zones, the homogeneity of land use and/or population, and appropriate sizes. But the range of traditional TAZs is too large to reflect the impact of the built environment on travel behavior [22]. Fortunately, with the wide use of commercial-map servers, POI data is easily available, which can offer plentiful point data of the built environment and can be transformed to fine scale. POI data and fine scale unit provide a new possibility for the studies of built environment and online car-hailing travel, but up to now, there are few related studies.

Thirdly, traditional quantitative analysis methods are dominated by a global regression model [5,9,14]. Although by applying a global regression model, scholars can quantify the influence of built environment relatively quickly and conveniently, the estimated parameters of this model do not vary with space [23]. However, the influence of environment variables may vary with urban forms and time [9], and those spatial analyses are important because ignoring spatial instability may lead to inconsistent parameters or inaccuracy of test results [24]. In addition, some authors have explored the spatial impacts of the built environment on car ownership and travel mode choice [25]. However, with a few exceptions, spatio-temporal variation is often neglected in most studies. The geographically weighted regression (GWR) model is an appropriate alternative model to capture spatial heterogeneity which can overcome this shortcoming [26]. It can be used to effectively reveal the spatial variation of influence coefficient across a study area [23]. Many scholars have applied this model in their studies, such as investigating the spatially varied built environment effects on community opportunity [27], identifying the role of light rail in driving land price up along the route [28], and analyzing the spatio-temporal influence of built environment on transit ridership [29]. However, minimal research effort has been exerted to estimate the association between built environment and online car-hailing travel.

Based on the aforementioned analysis, this paper intends to investigate the impact of the built environment on online car-hailing utilizing travel data published by the DiDi company and POI data in Chengdu collected from Gaode Map with the GWR model.

3. Data Description

3.1. Study Area and Data Sources

To promote the development of scientific research in the field of intelligent transportation and to create greater value for society, DiDi company provided desensitization online car-hailing travel data in their GAIA plan, which includes one-month trajectory data and order data in the northeast of Chengdu, China (30.65 to 30.72N, 104.04 to 104.12E). As travel traffic has a certain regularity and periodicity, and so does the online car-hailing travel, we chose one set of weekday data with 188746 trips to represent weekday travel. A trip order includes pickup and drop-off location and time information. The research area of this paper is consistent with the data coverage area. In order to investigate the impact of the built environment on online car-hailing travel on a fine scale, a 0.5 km $\times$ 0.5 km grid was used as the analysis unit, and the study area was divided into 289 grids (see Figure 1a).

The research area included Jinjiang district, Jinniu district, Chenghua district, and Qingyang district (see Figure 1b.) Jinjiang district is a "prosperous business district" with a long history. It has Chunxi road, which is the century golden street, and Tianfu square, which is the heart of the city, and the mixed degree of land use in the Jinjiang district is relatively high. Qingyang district is located in the west of Chengdu city. There are Broad and Narrow Alley, Muma City Market and other business districts in the study area. Urban land in the Qingyang district is dominated by commercial and residential land, with a relatively dense road network and well-developed public transport facilities. Located in the northwest of Chengdu, Jinniu district has the largest Southwestern China comprehensive transportation hub—Chengdu north railway station. Chenghua district is located in the eastern region, most of which is outside the second ring road. The road network density and the number of public transport facilities are relatively sparse.

POI data was acquired from Gaode Map, and a total of 38461 POIs were obtained. There are 12 types of POI data: bus station POI, education and culture POI, recreation and entertainment POI, life service POI, shopping service POI, corporate business POI, residential district POI, accommodation service POI, catering service POI, government and administration POI, medical POI, and scenic zone

POI (see Figures 2 and 3). In addition, the road network data come from OpenStreetMap (OSM), and the demographic data come from the sixth nationwide population census.

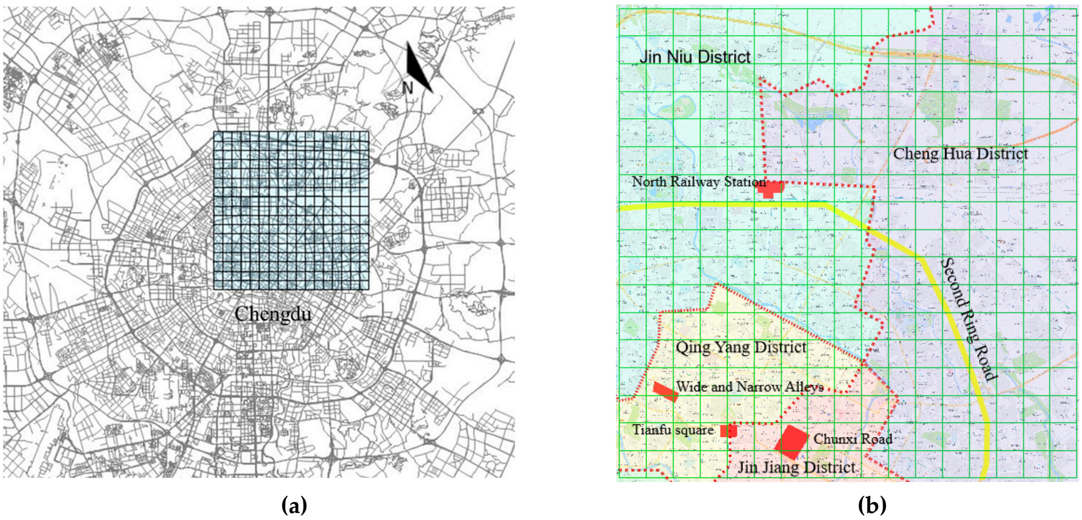


Figure 1. Study area. (**a**) Spatial grids of study area; (**b**) general situation of study region.

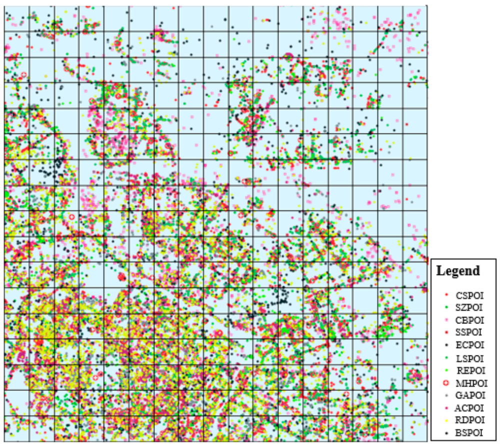


Figure 2. Distribution of points of interest (POIs) in the study area.

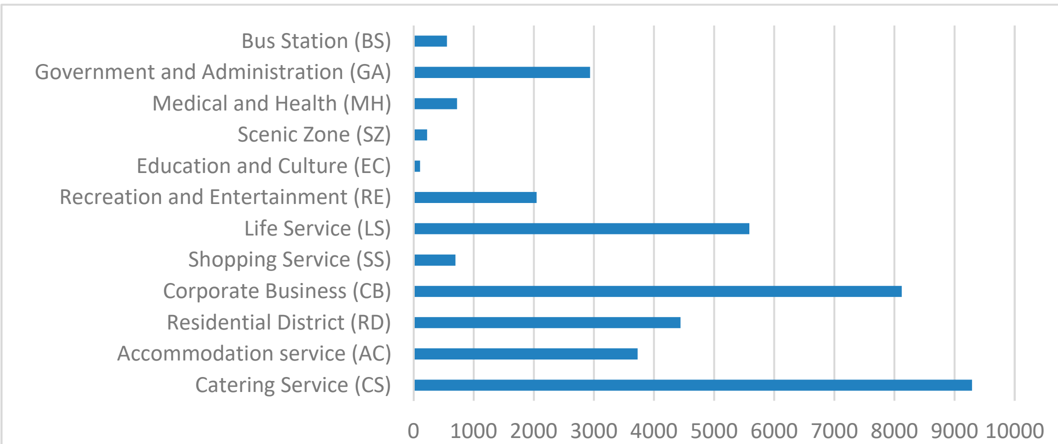


Figure 3. Total number of POIs in each category.

3.2. Independent Variable

The built environment refers to various buildings and urban spaces which are different from the natural environment, especially those that can be changed though policies and human behavior, and the mostly widely used descriptive dimension is drawn from the famously termed "five Ds" by Ewing and Cervero (2010) [12]. In this paper, based on previous research and characteristics of POI data, we firstly chose the "five Ds" and all types of POI data as the initial variables (see Table 1). To reduce the magnitude gap between variables, we applied a logarithmic transformation of all variables.

Table 1. Main indicators of the five Ds.

Variables	Main Indicators of Previous Studies	Indictor Variables of this Paper
Density	Population density, employment density	Population density
Diversity	Land-use mix, job-housing imbalance	Land-use mix
Design	Intersection density, neighborhood, road density	Road density
Destination accessibility	Accessibility to jobs, distance to CBD	Distance to CBD
Distance to transit	Bus stop density, distance to transit stop	Bus station POI
POI Category	–	The remaining 11 types of POI

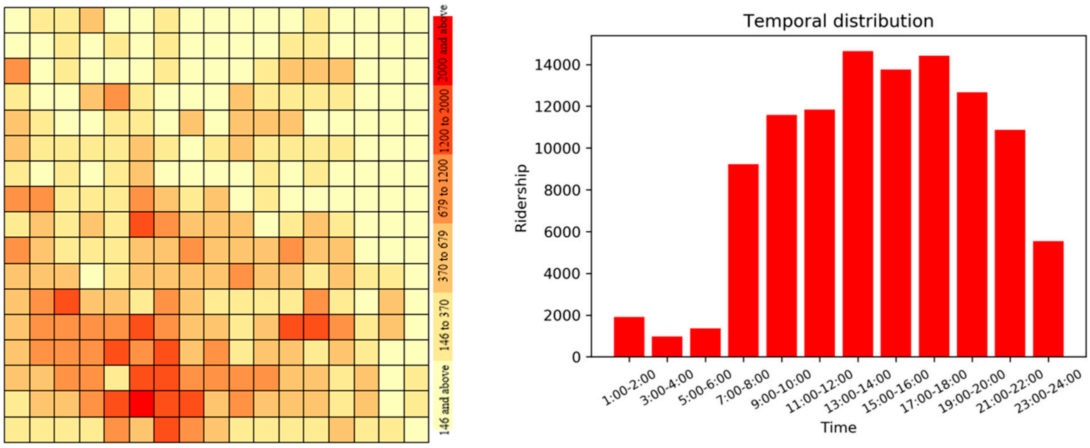
All initial variable measures are straightforward except for the "land-use mix". The Herfindahl–Hirschman index (HHI) is widely used to measure industry concentration in economics, and in addition, it can be used to reflect diversity [30]. Therefore, this paper chose the HHI to represent "land-use mix". The calculation formula of the HHI is shown in Equation (1). A small HHI value indicates a greater mixability, and vice versa.

$$\mathrm{HHI_i} = \sum_{j=1}^{N} \left(\mathrm{X_{ij}}/\mathrm{X_i}\right)^2, \tag{1}$$

where $\mathrm{X_i}$ is the total POI in grid i and $\mathrm{X_{ij}}$ is the total POI of category j in grid i.

3.3. Dependent Variable

VMT is a common explanatory variable in prior literature [12]. But this variable is more suitable for car travel, walking travel, and transit travel. In order to investigate built environment factors that affect online car-hailing travel, we chose boarding ridership of every grid as the explanatory variable. The boarding ridership is the number of trips originated in each cell. Figure 4 shows the spatial-temporal distribution of pick-up ridership on 3rd November 2016, in which hot areas are concentrated near Chunxi Road and Wanda Plaza, and areas with less travel are concentrated along the eastern railway. The number of ridership is very small at night, increases sharply in the morning, and then peaks at noon. The spatio-temporal variation of ridership indicates that the influence of built environment on online car-hailing travel may vary with time and space. To investigate this influence more deeply, a high peak (13:00–14:00) and low peak (3:00–4:00) time were respectively selected.



(a) **(b)**

Figure 4. Spatial-temporal distribution of pick-up ridership of online car-hailing travel. (**a**) Spatial distribution; (**b**) temporal distribution.

4. Methodology

4.1. Correlation and Multicollinearity

As suggested in Table 1, each variable can be expressed by different indicators. There aretotal of 16 initial indicators, including population density, land-use mix, road density, distance to CBD, bus station POI, education and culture POI, recreation and entertainment POI, life service POI, shopping service POI, corporate business POI, residential district POI, accommodation service POI, catering service POI, government and administration POI, medical POI and scenic zone POI. None of which can fully represent the built environment alone, but which together may overstate it, because an exact correlation or high correlation may exist between indicators. Therefore, we apply the stepwise regression model to identify the important variables without multicollinearity [31]. Then the variance inflation factor (VIF) is also calculated to quantify the multicollinearity of selected variables, and variables with VIF greater than 10 are deleted.

4.2. Spatial Autocorrelation

One of the main drawbacks for the global model is that the effects of explanatory variables are assumed to be homogenous across space. However, these effects may be spatially nonstationary due to the different spatial distribution patterns of variables. Spatial autocorrelation can help to understand the degree of similarity between a variable and the same variable nearby. Moran's I can measure this spatial autocorrelation [32]. To investigate the spatial autocorrelation of variables, the Moran's I of the variable is calculated in this paper.

4.3. Geographically Weighted Regression

The GWR model is widely used to investigate the spatial nonstationarity, which allows for coefficients to alter over space. The model is calculated as Equation (2) [23].

$$y_i = a_{i0} + \sum_k a_{ik} x_{ik} + \varepsilon_i, \quad (2)$$

where y_i refers to the ridership in grid I, denotes the intercept of grid I, a_{ik} represents the coefficient of x_{ik} at grid i, x_{ik} represents the kth variable of grid i, and ε_i is the error term of grid i. The most crucial parameter in GWR is a_{ik}, which varies in space and can capture spatial heterogeneity. It can be estimated using Equation (3).

$$\hat{a}_i = (X^T W_i X)^{-1} X^T W_i Y, \tag{3}$$

here W_i is an $n \times n$ diagonal matrix (see Equation (4)) whose off-diagonal elements are zero, and whose diagonal elements is W_{ij}; W_{ij} is the spatial attenuation coefficient, which can be calculated using the Gaussian function (see Equation (5)), and if i and j overlap, the value of W_{ij} will be unity, and the value of W_{ij} will decrease according to a Gaussian curve as the d_{ij} increase.

$$W_i = diag(W_{i1}, W_{i2}, \ldots, W_{in}) \tag{4}$$

$$W_{ij} = \exp\left(-(d_{ij}/b)^2\right) \tag{5}$$

In this function, d_{ij} is the distance between grid i and grid j. b is the bandwidth, which represents the attenuation parameter of W_{ij}. The larger the bandwidth is, the slower the W_{ij} decreases with the increase of distance, and vice versa. In this paper the bandwidth is chosen based on the Akaike information criterion (AICc) [33], which is widely used to measure the quality of a statistical model.

5. Model Results and Discussion

Table 2 presents descriptive statistics of the selected variables after applying a stepwise regression model. In the period 3:00 to 4:00, only three variables have significant influence on online car-hailing pick-up behavior: recreation and entertainment POI, residential district POI and bus station POI. Between the period 13:00 and 14:00, boarding behavior is affected by six variables: land-use mix, bus station POI, residential district POI, catering service POI, shopping service POI and corporate business POI. Table 3 shows the Moran's I values, which are between 0.1 to 0.7 and indicate a positive spatial auto-correlation of all variables.

Table 2. Descriptive statistics of selected factors.

Variables	Minimum	Maximum	Mean	Std	Variables in Period 3:00–4:00	Variables in Period 13:00–14:00
Land-use mix	0.14	1.00	0.29	0.20		√
Bus Station POI	0.00	8.00	1.92	1.42		√
Residential District POI	0.00	21.00	6.61	4.49	√	√
Catering Service POI	0.00	216.00	32.15	33.80		√
Shopping Service POI	0.00	20.00	2.42	2.70	√	√
Corporate Business POI	0.00	266.00	28.10	39.39		√
Recreation and Entertainment POI	0.00	65.00	7.09	8.89	√	

The global model (OLS) is firstly used to identify the significant built environment variables which influence the online car-hailing travel, and the results are summarized in Table 4. The adjusted R^2 for the OLS model in different periods is 0.63 and 0.80, which indicate a middle and high degree of fit to data, respectively. The VIF values for all variables are between 1 and 5, which means that the selected factors show no strong multicollinearity. According to the coefficient values, in the period 3:00 to 4:00, the online car-hailing boarding behavior is mostly affected by recreation and entertainment POI, followed by residential district POI, then shopping service POI. However, these three variables are nonhomogeneous over space, as shown in Table 3, which makes some coefficients in the global model hard to explain. Do recreation and entertainment POI have the greatest impact on online car-hailing boarding behavior in every study area, even in the areas without entertainment facilities? The same question exists for the period 13:00 to 14:00. The single result of OLS model does not represent the relationships between the built environment and online car-hailing travel, which are invariant over the study region, and due to this, further studies using the GWR model are necessary.

Table 3. Moran's I value for candidate indicator variables.

Variables	Moran's Index	Z-Score	P-Value
Land-use mix	0.261366	23.36248	0.000
Bus Station density	0.114854	10.31088	0.000
Residential District	0.62523	54.73396	0.000
Catering Service	0.411	36.047	0.000
Shopping Service	0.262575	23.15931	0.000
Corporate Business	0.455918	40.00732	0.000
Recreation and Entertainment	0.389449	34.21143	0.000
Trips in 3:00–4:00	0.310682	27.34691	0.000
Trips in 13:00–14:00	0.423656	37.244337	0.000

Table 4. Estimation results for global models (OLS).

Variable	3:00 to 4:00			13:00 to 14:00		
	Coefficient	t-Stat	VIF	Coefficient	t-Stat	VIF
Intercept	−0.06	−1.98	–	0.52	7.02	–
Land-use mix	–	–	–	−0.41	−3.80	1.87
Bus Station density	–	–	–	0.39	4.87	1.32
Residential District	0.22	4.01	2.23	0.33	4.38	3.36
Catering Service	–	–	–	0.25	4.70	4.81
Shopping Service	0.21	3.59	2.21	0.28	3.66	2.51
Corporate Business	–	–	–	0.19	4.84	2.25
Recreation and Entertainment	0.41	8.41	2.74	–	–	–
R^2	0.65			0.81		
Adjusted R^2	0.63			0.80		
AICc	−23.78			63.15		
Residual sum of squares	15.04			19.88		

The GWR results for online car-hailing boarding behavior in the period 3:00 to 4:00 and 13:00 to 14:00 are presented in Table 5. Because the sample size was too large, Table 5 only shows values as minimum, lower quartile, median, upper quartile maximum, and standard deviation of the coefficient. In order to check the non-stationary nature of the coefficient, Moran's I value, Z-scores and P-values are also listed in Table 5, which imply that the parameters of all variables exhibit significant spatial variation.

Table 5. Estimated geographically weighted regression (GWR) in period 3:00 to 4:00 and period 13:00 to 14:00.

(a) Estimated GWR in Period 3:00 to 4:00									
Variable	Minimum	Lower quartile	Median	Upper quartile	Maximum	SD of coefficient	Moran I of coefficient	Z-score of coefficient	P-value of coefficient
Intercept	−0.63	−0.30	−0.12	−0.03	0.00	0.18	0.94	51.69	0.000
Recreation and Entertainment POI	0.18	0.33	0.38	0.46	0.76	0.13	0.93	51.57	0.000
Residential District POI	0.12	0.24	0.30	0.40	0.71	0.59	0.89	49.54	0.000
Shopping Service POI	−0.01	0.15	0.39	0.40	0.39	0.07	0.87	48.14	0.000
(b) Estimated GWR in period 13:00 to 14:00									
Variable	Minimum	Lower quartile	Median	Upper quartile	Maximum	SD of coefficient	Moran's I of coefficient	Z-score of coefficient	P-value of coefficient
Intercept	0.33	0.51	0.55	0.58	0.65	0.06	0.78	72.46	0.000
Land-use mix	−0.73	−0.52	−0.41	−0.32	−0.08	0.15	0.82	75.89	0.000
Bus Station POI	0.14	0.25	0.35	0.50	0.79	0.16	0.86	79.27	0.000
Residential District POI	0.23	0.29	0.33	0.35	0.47	0.05	0.82	76.70	0.000
Catering Service POI	0.12	0.16	0.22	0.30	0.38	0.07	0.86	79.33	0.000
Shopping Service POI	0.21	0.28	0.32	0.34	0.36	0.04	0.83	77.16	0.000
Corporate Business POI	0.14	0.18	0.19	0.20	0.25	0.02	0.68	63.54	0.000

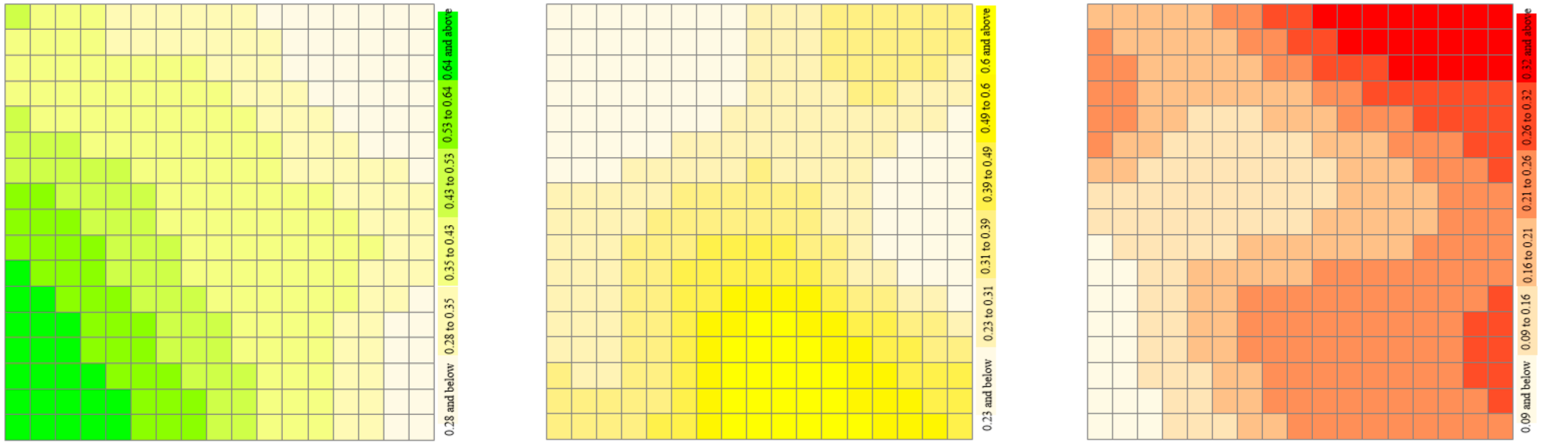
As is shown in Table 6, in the period 3:00 to 4:00, the adjusted R^2 is 0.67 for the GWR model, which improves by 0.03 compared with the global model. In the period 13:00 to 14:00, the GWR model improves the adjusted R^2 from 0.80 to 0.82, and the reduction of the AICc and residual sum of squares prove that the GWR model is more superior to the OLS model.

Table 6. Diagnostic information of OLS and GWR.

Diagnostics	3:00 to 4:00		13:00 to 14:00	
	OLS	GWR	OLS	GWR
R^2	0.65	0.71	0.81	0.84
Adjusted R^2	0.63	0.67	0.80	0.82
AICc	−23.78	−31.59	63.15	50.55
Residual sum of squares	15.04	12.49	19.88	17.45
Bandwidth	–	1508		2670
F-value	–	1.713		2.03

Figure 5a presents the coefficient spatial distribution of recreation and entertainment POI, which shows a reduction from southwest to northeast like waves. In the southwest area, online car-hailing travel is mainly near the entertainment facilities, such as chess room, KTV, and bars. A possible explanation is that most of those passengers in the southwest call for online cars after partaking in the local nightlife. While in the south-central region of the study area, the most influential factor is residential district (see Figure 5b). This indicates that a higher number of residential districts is expected to bring more online car-hailing travel. What is puzzling is that, as shown in Figure 5c, the confidence of the shopping service POI is highest in the northeast region, but there is no store open all night in this area. By checking the distribution of shopping service POI and boarding points, these stores are all in the residential area, and so are the boarding points. Therefore, online car-hailing travel is affected by residential district, which can be proved by the northeast region in Figure 5b.

The spatial distribution of estimated parameters in the period 13:00 to 14:00 is displayed in Figure 6. Figure 6a reveals that land-use mix has a strong positive effect on online car-hailing travel, especially in the southeast region, that is, there is more online car-hailing travel in the areas with a high degree of land-use mix. However, this finding is inconsistent with previous studies investigated by Cervero (1996), Mccormack et al. (2001), Munishi (2016), Yin Chaoying (2018), Xie Weihan (2018) and others, who recognized land-use mix as an effective strategy to reduce car travel by incorporating sufficient living facilities (e.g., presence of offices, residences, retail, and other uses) [7,19,34–36]. Chunxi Road, a famous commercial zone in Chengdu, has a high level of land-use mix with numerous shopping stores, recreational facilities, office buildings, residential buildings, a hospital, etc. The VMT for a nonwork trip is lower in areas with a high degree of land use mix, according to the study carried out by Kockelman (1997) [37]. However, online car-hailing travel is higher in this area. A possible explanation is that areas with a higher degree of diversity are more attractive than other regions. This inference can be supported by the work of Randall Crane (1996) who proposed that the improved accessibility to multiple destinations increases nonwork trips due to low trip costs and, in this paper, because it is attractive [38].



(a) **(b)** **(c)**

Figure 5. Coefficient spatial distribution of variables in 3:00 to 4:00. (**a**) Coefficient spatial distribution of recreation and entertainment POI; (**b**) coefficient spatial distribution of residential district POI; and (**c**) coefficient spatial distribution of shopping service POI.

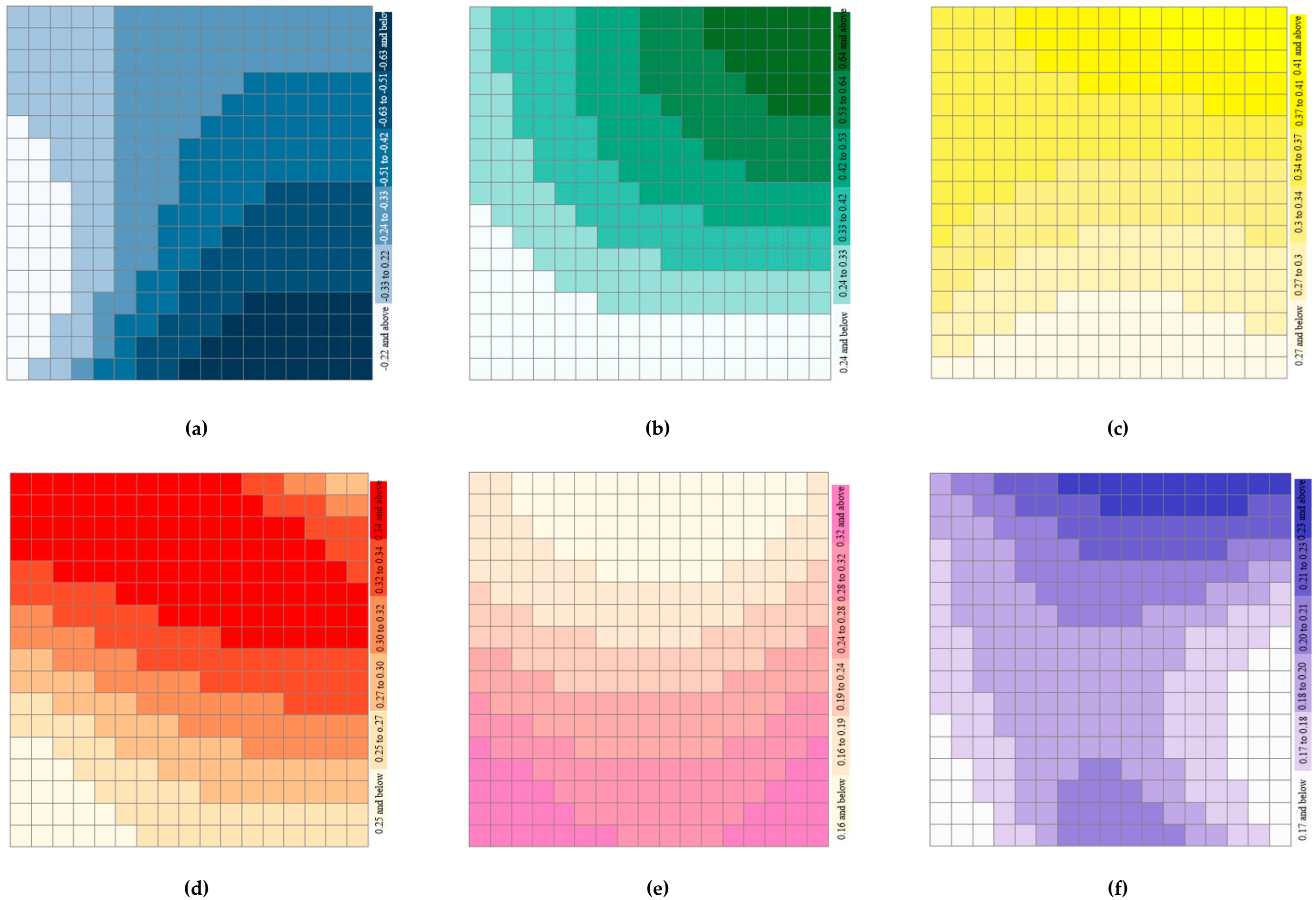


Figure 6. Coefficient spatial distribution of variables in 13:00 to 14:00. (**a**) Coefficient spatial distribution of land-use mix; (**b**) coefficient spatial distribution of bus station POI; (**c**) coefficient spatial distribution of residential district POI; (**d**) coefficient spatial distribution of shopping service POI; (**e**) coefficient spatial distribution of catering service POI; and (**f**) coefficient spatial distribution of corporate business POI.

Figure 6b shows that the coefficient of bus station POI decreases from northeast to southwest. This implies that the effect of bus station POI on online car-hailing travel is significant in the outskirts, especially in the east outside the second ring road. Online car-hailing travel is always generated near the bus stations in this area. Therefore, it can be speculated that online car-hailing travel is a supplement to bus trips due to its flexibility and convenience. This supplement is not obvious within the second ring road, mainly because public transport in the urban central area is more convenient with higher bus station density and bus line density. This finding is contrary to the conclusion of Yang et al. (2018), who noted that taxi trips do not tend to complement bus trips, maybe because some bus passengers have lower income [14]. Although taxi travel and online car-hailing travel are different, they have a lot in common, such as they both provide a flexible door-to-door service. Therefore, the relationships between bus trip and taxi trip or online car-hailing travel can be compared together. But how can these conflicting conclusions be reconciled? Perhaps because the study area is different, one in America and the other in China. However, more empirical research is needed to verify this inference.

Similar to Figure 6b, a parameter reduction of residential district POI from northeast to southwest is also shown in Figure 6c, and the positive value of parameters indicates that residential district POI has a strong influence on online car-hailing travel. This finding is consistent with the conclusion by Yang et al. (2018) that residential density would contribute to taxi trips positively [14]. However, the contribution of residential density is unbiased over space in his study, which may mask the different effects in different areas. In this research, the influence in the northeast area is strong, but the residential district POI are sparse. While in the dense areas of residential district POI, this positive effect is more muted. A possible reason is that in the northeast area, land use type is relatively unitary, mainly including residential, industrial, and undeveloped land, and online car-hailing travel is mainly around residential areas. In the southeast this phenomenon is not obvious, so the effect of residential districtPOI is stronger in the northeast.

Interestingly, the area where online car-hailing travel is most effected by shopping service POI is not Chunxi Road, but the north area (see Figure 6d). Actually, Chunxi Road does produce numerous online car-hailing travel, but the impact of shopping services should be understood more deeply. Because in these prosperous areas, there are not only many stores, but also other facilities, such as offices, residential, residential, etc. Trips in these areas may not only be attracted by shops. This finding is consistent with the thesis proposed by Qian et al. (2015), who noted that the land use of commercial areas is highly diversified and its effect on taxi trips is insignificant [39]. The coefficients are the highest in the northern region, and the reason is likely to be related to the distribution of the types of shops. Shops in the north area are mainly around residential area, whose influence in this area is relatively high, and the reason has been explained above.

Figure 6e gives a perfect symmetrical distribution of coefficients for catering service POI. The coefficient values are higher in the south area, especially in Wide and Narrow Alleys, which are the famous historic blocks and includes many snack outlets. Undoubtedly, it attracts many online car-hailing trips and so the coefficient is high. Figure 6f indicates that the influence of corporate business close to Tianfu square in the south area and furniture market in the north area is higher than in other places. Although the correlation is positive in general, areas with more office blocks may generate more online car-hailing trips.

In addition to the factors mentioned above, some variables were excluded because they are not significant to online car-hailing travel, such as population density, road density, distance to CBD, and some categories of POI. However, previous studies have obtained different conclusions. For example, some research shows that population density has a significant effect on car trips. The increments in the density of people contribute to the increase in taxi trips (Yang et al., 2018) and the decrease in vehicle kilometers of travel (Choi, 2018) [5,14]. After checking population density data, the probable explanation for this is that the variation of population density in most study areas is relatively low, except in the southwest area and northeast area (see Figure 7). In addition, population data was derived from the sixth census, which is conducted every ten years and is based on administrative districts. However, in this paper, the research area is divided into hexagons, and the ride-hailing industry has only emerged in recent years. Such population data may fail to support fine-grained spatial analysis, so the effect of population distribution on online car-hailing travel is not significant. Qian et al. (2015) indicates that areas with lower road density may bring more taxi trips, but care is needed when transplanting this conclusion to online car-hailing travel [39], as it is regarding distance to CBD, which was found to have a large influence on vehicle car use [17] but had no obvious effect on online car-hailing travel in this paper.

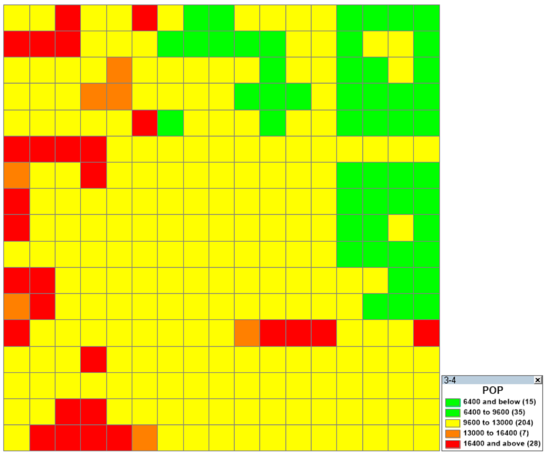


Figure 7. Spatial distribution of population density.

6. Conclusions

As a key component for urban mobility, online car-hailing travel is undergoing a period of rapid growth. However, limited efforts have been made to understand the relationships between the built environment and online car-hailing travel, despite this being a pressing need to provide basic support for government decision-making. This paper applies the GWR model to identify the main factors of online car-hailing travel in Chengdu and the spatial variation of the coefficients. The results of the analyses are discussed below.

Firstly, recreation and entertainment POI and residential district POI are the most influential factors for night online car-hailing travel. The southwest area was the region affected mostly by recreation and entertainment POI, which is where many entertainment venues can be found. The south-central area was mostly affected by residential district POI, where residential areas are relatively highly concentrated. The grasp of these distribution features can help ride-hailing companies operate more efficiently. Upgrading dynamic ride-matching algorithms that consider the influence of the built environment will improve the order receiving efficiency of drivers and reduce the waiting time or detouring time.

Secondly, in rush hour, land-use mix has a positive effect on online car-hailing travel. Although previous research proved that improving the degree of land-use mix can reduce car travel frequency, areas with a high level of diversity may be more attractive than other regions, hence attracting more online car-hailing travel. Therefore, the optimal conditions of land-use mix requires more research when dealing with urban planning or traffic management issues.

Thirdly, the findings of this paper suggest that online car-hailing travel may be a complementary mode for buses, especially in eastern areas outside the second ring road. This relationship deserves more attention in the process of well-connected multiple modal transportation system development.

Fourthly, population density, road density, distance to CBD, and some categories of POI have no appreciable impact on online car-hailing travel in our study, while these variables are proved to be important in other literature. Maybe when selecting the appropriate variable, it should be adapted to local conditions rather than simply being transplanted.

To enlighten future research, the limitations of this paper should be noted as follows.

First, our study only utilizes boarding information to characterize travel behavior. Further studies may expand travel behavior elements to include travel time, travel distance, and land use characteristics of destination. This abundance of diverse factors could also shed light on strong relationships between built environment and online car-hailing travel.

Second, this paper uses first level classification of POIs to represent the urban built environment. However, POIs with second level subdivisions may have different effects on online car-hailing travel. For example, residential district POIs can be subdivided into business-living building POIs and residential POIs. Land use of business-living is more mixed, and the complexity of its influence on travel behavior is higher than that of pure residential land. Thus, more research on fine-grained built environment classification is needed in the future.

Third, in this paper, peak period and low peak period of the working day are selected for analysis, while in our future research, more analysis on time frames will be carried out to capture the different influence of built environment on online car-hailing travel at different times, and we will also validate whether our findings hold in other cities.

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References

1. 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* **2015**, *45*, 168–178. [CrossRef]
2. Wang, M.; Mu, L. Spatial disparities of Uber accessibility: An exploratory analysis in Atlanta, USA. *Comput. Environ. Urban Syst.* **2018**, *67*, 169–175. [CrossRef]
3. Dong, Y.; Wang, S.; Li, L.; Zhang, Z. An empirical study on travel patterns of internet based ride-sharing. *Transp. Res. Part C Emerg. Technol.* **2018**, *86*, 1–22. [CrossRef]
4. Wang, D.; Chai, Y.; Li, F. Built environment diversities and activity–travel behaviour variations in Beijing, China. *J. Transp. Geogr.* **2011**, *19*, 1173–1186. [CrossRef]
5. Choi, K. The influence of the built environment on household vehicle travel by the urban typology in Calgary, Canada. *Cities* **2018**, *75*, 101–110. [CrossRef]
6. Acker, V.V.; Witlox, F. Commuting trips within tours: How is commuting related to land use? *Transportation* **2011**, *38*, 465–486. [CrossRef]
7. Cervero, R.; Kockelman, K. Travel demand and the 3Ds: Density, diversity, and design. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [CrossRef]
8. Guo, J.Y.; Bhat, C.R.; Copperman, R.B. Effect of the Built Environment on Motorized and Nonmotorized Trip Making: Substitutive, Complementary, or Synergistic? *Transp. Res. Rec. J. Transp. Res. Board* **2015**, *2010*, 1–11. [CrossRef]
9. Zhou, B.; Kockelman, K.M. Self-selection in home choice: Use of treatment effects in evaluating relationship between built environment and travel behavior. *Transp. Res. Rec. J. Transp. Res. Board* **2008**, *2077*, 54–61. [CrossRef]
10. Kitamura, R.; Mokhtarian, P.L.; Laidet, L. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. *Transportation* **1997**, *24*, 125–158. [CrossRef]
11. Reid Ewing, R.C.; Cervero, R. Travel and the built environment—Synthesis. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1780*, 265–294.
12. Ewing, R.; Cervero, R. Travel and the Built Environment. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]

13. Wang, Z.; He, S.Y.; Leung, Y. Applying mobile phone data to travel behaviour research: A literature review. *Travel Behav. Soc.* **2017**, *11*, 141–155. [CrossRef]
14. Yang, Z.; Franz, M.L.; Zhu, S.; Mahmoudi, J.; Nasri, A.; Zhang, L. Analysis of Washington, DC taxi demand using GPS and land-use data. *J. Transp. Geogr.* **2018**, *66*, 35–44. [CrossRef]
15. Ge, W.; Shao, D.; Xue, M.; Zhu, H.; Cheng, J. Urban Taxi Ridership Analysis in the Emerging Metropolis: Case Study in Shanghai. *Transp. Res. Procedia* **2017**, *25*, 4920–4931. [CrossRef]
16. Ding, C.; Wang, D.; Liu, C.; Zhang, Y.; Yang, J. Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. *Transp. Res. Part A Policy Pract.* **2017**, *100*, 65–80. [CrossRef]
17. Zegras, C. The Built Environment and Motor Vehicle Ownership and Use: Evidence from Santiago de Chile. *Urban Stud.* **2010**, *47*, 1793–1817. [CrossRef]
18. Munshi, T. *Built Form, Travel Behaviour and Low Carbon Development in Ahmedabad, India*; Institute for Geo-information Science & Earth Observation: Enschede, The Netherlands, 2013.
19. Munshi, T. Built environment and mode choice relationship for commute travel in the city of Rajkot, India. *Transp. Res. Part D Transp. Environ.* **2016**, *44*, 239–253. [CrossRef]
20. Cervero, R. The built environment and travel: Evidence from the United States. *Eur. J. Transp. Infrastruct. Res.* **2003**, *3*, 119–137.
21. Cervero, R. Built environments and mode choice: Toward a normative framework. *Transp. Res. Part D Transp. Environ.* **2002**, *7*, 265–284. [CrossRef]
22. Wu, C.; Ye, X.; Ren, F.; Du, Q. Check-in behaviour and spatio-temporal vibrancy: An exploratory analysis in Shenzhen, China. *Cities* **2018**, *77*, 104–116. [CrossRef]
23. Fotheringham, A.S.; Charlton, M.E.; Brunsdon, C. Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. *Environ. Plan. A* **1998**, *30*, 1905–1927. [CrossRef]
24. Anselin, L.; Griffith, D.A. Do spatial effecfs really matter in regression analysis? *Pap. Reg. Sci.* **1988**, *65*, 11–34. [CrossRef]
25. Ding, C.; Wang, Y.; Tang, T.; Mishra, S.; Liu, C. Joint analysis of the spatial impacts of built environment on car ownership and travel mode choice. *Transp. Res. Part D Transp. Environ.* **2018**, *60*, 28–40. [CrossRef]
26. Brunsdon, C.; Fotheringham, A.S.; Charlton, M.E. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geogr. Anal.* **2010**, *28*, 281–298. [CrossRef]
27. Wang, C.H.; Chen, N. A geographically weighted regression approach to investigating the spatially varied built-environment effects on community opportunity. *J. Transp. Geogr.* **2017**, *62*, 136–147. [CrossRef]
28. Mulley, C.; Tsai, C.H.; Ma, L. Does residential property price benefit from light rail in Sydney? *Res. Transp. Econ.* **2018**, *67*, 3–10. [CrossRef]
29. Ma, X.; Zhang, J.; Ding, C.; Wang, Y. A geographically and temporally weighted regression model to explore the spatiotemporal influence of built environment on transit ridership. *Comput. Environ. Urban Syst.* **2018**, *70*, 113–124. [CrossRef]
30. Palan, N. *Measurement of Specialization—The Choice of Indices*; FIW Working Paper; Research Centre International Economics: Vienna, Austria, 2010.
31. Fritz, M.; Berger, P.D. *Can You Relate in Multiple Ways? Multiple Linear Regression and Stepwise Regression*; Elsevier Inc.: Amsterdam, The Netherlands, 2015; pp. 239–269.
32. Moran, P.A. Notes on continuous stochastic phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
33. Akaike, H. Information theory and an extension of the maximum likelihood principle. In *International Symposium on Information Theory*; Springer: New York, NY, USA, 1973.
34. Mccormack, E.; Rutherford, S.; Wilkinson, M. Travel Impacts of Mixed Land Use Neighborhoods in Seattle, Washington. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1780*, 25–32. [CrossRef]
35. Yin, Y.; Shao, C.; Wang, X. Influence of Land Use Mixture on Travel Mode Choice. *J. Beijing Univ. Technol.* **2018**, *44*, 1227–1232.
36. Xie, W.; Zhou, S. The spatial-Temporal-Nonstationary Effect of Built-Environment on Taxi Demand. *Mod. Urban Res.* **2018**, *12*, 22–29.
37. Kockelman, K.M. Travel Behavior as Function of Accessibility, Land Use Mixing, and Land Use Balance: Evidence from San Francisco Bay Area. *Transp. Res. Rec. J. Transp. Res. Board* **1997**, *1607*, 116–125. [CrossRef]

38. Crane, R. *Cars and Drivers in the New Suburbs: Linking Access to Travel in Neotraditional Planning*; University of California Transportation Center Working Papers; University of California: Berkeley, CA, USA, 1994; Volume 62, pp. 51–65.
39. Qian, X.; Ukkusuri, S.V. Spatial variation of the urban taxi ridership using GPS data. *Appl. Geogr.* **2015**, *59*, 31–42. [CrossRef]