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How Does the Built Environment in Urban Villages Affecting Ride-Sourcing Commuting Trips Interacting with the Spatial Dependence Effect

Le Yu [1], Xiaodan Li [2] and Qin Luo [1,*]

[1] College of Urban Transportation and Logistics, Shenzhen Technology University, Pingshan District, Shenzhen 518118, China; yule@sztu.edu.cn
[2] School of Architecture, Harbin Institute of Technology (Shenzhen), Shenzhen University Town, Nanshan District, Shenzhen 518055, China
* Correspondence: luoqin@sztu.edu.cn

Abstract: Urban renewal provides opportunities to improve urban transport structures during the process of improving built environments. It is necessary to clarify the impact of different elements of the built environment on travel behaviors in the context of urban village renewal. This paper presents a microscopic perspective of individual travel behavior by proposing analytical frameworks to investigate travel behavior in terms of DiDi commuting trips. Considering the effect of spatial dependence, a Spatial Durbin Error Model was established, incorporating a spatial lag and spatial error. Traveling information was employed from the ride-sourcing company DiDi during the morning and evening peaks within in the urban village areas and workplaces of Shenzhen, and the variables of a built environment were scaled within travel analysis zones (TAZs). The results show that the impacts of the built environment on ride-sourced commuting were different between job and housing locations, with more influential factors in residential locations (urban villages). On the other hand, working locations had an influential magnitude more than twice that of residential locations. Alongside that, due to the spillover effect, it was more effective to hinder ride-sourced commuting and promote green traveling modes by increasing the number of bus stops. The findings provide some insights into transit-oriented urban renewal. Therefore, when transforming urban villages, an emphasis should be placed on the enhancement of transit availability, and the mixed land use could be considered last due to limited time and funds.

Keywords: built environment; urban village; transit-oriented renewal; spatial dependence; ride-sourced trips; urban transportation

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1. Introduction

Among the components of urban planning, built environments implicitly guide people's travel habits. Built environments have a "lock-down effect" on residents' travel behaviors [1], as travel behaviors are determined by the spatial structure and functional layout of built environments at the macro level. Therefore, optimization of a built environment is regarded as an important means to shape a low-carbon urban spatial structure, guiding the green and low-carbon travel patterns of residents and combatting climate change issues.

Urban renewal provides opportunities for traffic improvement, accelerating the pace of its progress and optimizing land use and the urban layout structure. Furthermore, urban renewal and traffic improvements can promote one another, interacting as both cause and effect. It must be carried out scientifically and orderly, under the control of traffic planning. As an important factor of urban renewal in the sustainable direction of urban development, transportation must be given sufficient attention. Therefore, it is necessary to clarify the

impact of different components of built environments on travel behaviors in the context of urban renewal.

China is one of the largest countries experiencing large-scale urban renewal. In many areas of the country, especially large- and medium-sized cities undergoing accelerated urbanization, the need for the renewal and regeneration of "urban villages" is particularly urgent, being critical targets. As informal residential communities, urban villages show many inconsistencies with the development of cities. The traditional renewal of urban villages often adopts demolition and reconstruction methods, which play important roles in improving land-use efficiency and promoting sustainable urban development [2,3]. However, as low-cost living spaces, urban villages accommodate a large number of urban employment and emigration populations from high-housing-cost areas, which improves the flexibility of urban development. At the same time, the high-density population of urban villages has relieved the trend of the job–housing imbalance and, hence, reduced the overall transportation cost of cities. Therefore, urban villages hold the position of a double-edged sword, and the issue of urban villages cannot be solved solely through demolition. Currently, differentiated and diversified renewal strategies are being developed, and the proportion of urban village demolishment and reconstruction is gradually becoming lower, which encourages the comprehensive renovation and functional regeneration of urban villages to promote organic and effective urban renewal.

Therefore, under these circumstances, new questions are arising in research relating to the relationship between travel behaviors and built environments. Although many related studies have been conducted in the context of developed societies, the situation in China is not understood sufficiently. Thus far, there is little research on the interaction between urban village and traffic structure optimization, especially regarding built environment characteristics, resident travel characteristics, and the relationship between built environments and resident travel behaviors involved in the process of urban village renewal. China has witnessed unprecedented urban development and regeneration over the past few decades. The regeneration in residential built environments and neighborhood type have resulted in changes to jobs–housing relationships and, ultimately, daily travel demands, providing an important context for studies of built environments and travel behaviors in urban China. In view of this, this research attempted to conduct theoretical analysis and empirical research on the effects of the built environment on travel behaviors in the context of urban village reconstruction in China to explore the relationship between built environment and travel behaviors. Our research aimed to explore an effective way to improve the conditions of the transport system by guiding the regeneration of the built environment in urban villages, helping provide better decision support for the organic renewal of urban villages and transport planning policies.

This study intends to focus on an urban village, which is one of the most remarkable regenerations in a neighborhood type in China, to examine its distinctive features and the uniqueness of the associations between travel behavior and the built environment. This study aimed at not only an in-depth investigation of the impacts of the built environment on travel behaviors but also conducting a targeted urban form in China to fill the vacancy in this research domain. From the microscopic perspective of individual travel behaviors, analytical frameworks were proposed to investigate travel behaviors utilizing DiDi commuting trip information. Considering the effect of spatial dependence, a Spatial Durbin Error Model was established, incorporating a spatial lag and spatial error. Traveling information was employed from the ride-sourcing company DiDi during the morning and evening peaks within urban village areas and workplaces of Shenzhen, and the variables of a built environment were scaled within travel analysis zones (TAZs).

2. Literature Review

A large number of studies have confirmed that a variety of built environment factors have a significant relationship with travel mode choice; some results support the development of new urbanism in changing residents' travel behaviors by developing a

more compact and mixed-use built environment, thereby reducing the negative impact of motor vehicle use [4–6]. However, the existing empirical results of the relationship between the built environment and travel behaviors are still controversial. For example, a study in Beijing found a significant relationship between land use, travel speed, and travel distance [7]; however, in a similar study in Los Angeles, the results differed [8]. Given the inconsistent empirical results, it is necessary to study the causes of such differences and the understanding of the relationship between the built environment and travel behaviors requires more in-depth research. The differences in some research conclusions may be the by-products of employing different methods, data, and empirical case cities or regions. In addition, a number of the more complex methodological issue may have also resulted in different empirical conclusions [9].

Spatial dependence is a main methodological problem that results in differentiation among empirical results. Spatial dependence refers to the correlation between sample observations in one area and observations in other areas [10]. Due to the location and diffusion of elements among regions, interactions, and mutual influence are formed in a geographic space, resulting in samples that are not independent in space. Thus, the correlation strength of the variable will be affected by the relative position and absolute position between the regions, indicating that there will be spatial interactions between economic and geographic behaviors [11]. Spatial correlation is mainly reflected within the lag term of the dependent variable and the error term within the spatial regression model. The two basic spatial econometric models are the spatial lag model and the spatial error model [12]. Alongside that, spatial dependence (spatial autocorrelation) occurs when observations at nearby locations tend to have similar characteristics [13].

Almost all spatial data have the characteristics of spatial dependence (spatial autocorrelation), that is, an economic geographic phenomenon or an attribute value of a regional spatial unit is related to the same phenomenon or attribute value of the spatial unit in the adjacent region [14]. The spatial correlation will lead to the distortion of data information and the biased traditional econometric analysis. Therefore, the spatial correlation test is the key to constructing a spatial econometric model and conducting spatial econometric analysis [15]. In spatial data analysis, no matter what spatial econometric model is used, it is necessary to test whether there is a spatial correlation between economic variables in advance [13,16].

In terms of research methods, because the characteristics of an urban built environment and the characteristics of online car travel have spatial attributes, the characteristics of uncertainty and spatial dependence are expressed in multi-scale space and time, so the methods of spatial econometrics should be used for reference.

After distinguishing between residential areas and work areas, Bhat introduced a multi-level cross-classification model to study the impact of the built environment on commuting mode selection. The existence of spatial dependence will weaken the impact of the built environment [17]. Schwanen et al. studied the influence of urban form on car travel time in the Netherlands, and the result proved that the travel mileage of private cars showed similarity in regions with similar locations [18]. Ding et al. used the cross-nested Logit structure that allows potential spatial correlation to describe the problem of simultaneous choice of travel destination and travel mode, and the results showed that for short-distance shopping trips, alternative plans for travel mode selection had high spatial correlation [19].

According to the literature review, it can be found that the previous research seldom focused on ride-sourcing travel mode which is partly due to the difficulty of obtaining ride-sourcing travel mode data. Moreover, research on the impact of the built environment on travel behavior often ignored the difference between residence and employment. Therefore, this paper will use the data of the Didi Chuxing platform in Shenzhen and the optimized spatial measurement method, while considering the characteristics of the built environment of residence and workplace, and reveal the urban built environment factors that affect the demand for ride-sourcing travel mode.

3. Materials and Methods

3.1. Spatial Dependence Effect of Urban Villages

Spatial dependence refers to the correlation between sample observations in one area and those in other areas. The theoretical basis is the first law of geography; that is, everything is related spatially, but similar things are more closely related. The degree of correlation among the observation data will be affected by the relative position and absolute position between the regions, indicating that there will be spatial interactions between economic and geographic behaviors in this context.

Built environment data of urban villages have spatial attributes, so the influence of spatial dependence cannot be ignored; thus, spatial dependence analysis is required. The spatial characteristics of economic variables are related to the spatial location, distance, and arrangement, as well as spatial measurement, estimation, testing, and prediction methods used to analyze the quantitative regularity of economic activities within space and time dimensions [20]. If the spatial effect is ignored, it may lead to an over- or underestimation of the impact of the built environment on travel behaviors [21,22].

The spatial hierarchy is determined by characteristics of the spatial structure of the data itself. Although built environment characteristics can be analyzed via deconstruction, whereby TAZ-level variables are assigned to each trip sample (individual) that they belong to, to be treated as one of the attributes of each traveler [8], the spatial characteristics of built environment variables cannot be ignored. However, in this research, the hierarchical structure of spatial data still existed, especially in the context of the reconstruction of urban villages. Therefore, mutual influence of geographic space, including spatial dependence and spatial heterogeneity, affected the transformations [23]. The following Figure 1 shows the spatial hierarchy of TAZs, urban villages. and individuals.

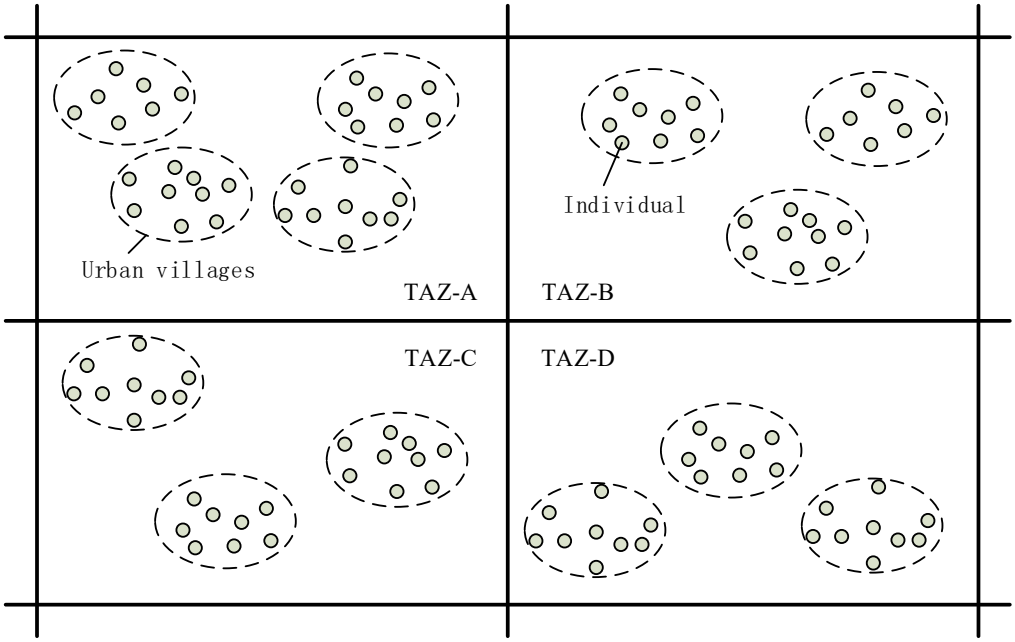


Figure 1. Spatial hierarchy of TAZs, urban villages and individuals.

From the perspective of the dynamic performance of space, the impact of spatial changes will inevitably have an effect since the regeneration of urban villages is a spatial action. In general, the distance between residential and employment places of residents is increasing. Price, environment, and job accessibility are the main reasons that affect residents' decision to move and change jobs. In the case of not having short-distance commuting, many residents choose to trade long-distance commutes for better living and employment conditions [24]. In addition, location and personal attributes also affect the spatial distance between residence and employment locations. In terms of location, the

attractiveness of employment in central urban areas is still outstanding. Usually, residents living close to the central area commute a short distance, and they tend to choose to relocate or choose another job within a short distance. Regarding personal attributes, the middle-income population moves and changes jobs relatively more frequently than other income groups [8]. On the macro level, the mismatch between urban residence and employment space, urban space expansion, structure of land under a single function, and individual socio-economic transformation affect the distance between residence and employment locations.

3.2. Statistical Description of the Raw Data

The data set comes from DiDi Chuxing Company (a ride-souring service company), Shenzhen branch. In terms of online car-hailing market share, DiDi Chuxing is the world's largest one-stop diversified travel platform, with nearly 300 million users in more than 400 cities in China at the end of 2017. According to various data, DiDi has more than 87% of China's private car market and more than 99% of the online taxi market. Therefore, to study the problem of ride-sourcing travel mode from a macro perspective of the city, the data of the DiDi travel platform used in this research is highly representative.

This research has obtained a total of 253,370 DiDi Travel data records in Shenzhen during the five working days (Monday–Friday) from 4 July 2016 to 8 July 2016. The DiDi Travel platform has defined travel time as three peak types, where "1" represents the morning peak and is defined as 7:00–10:00, "3" represents the evening peak and is defined as 17:00–20:00, and "2" is defined as 10:00–17:00. This research focuses on commuting travel of urban villages, so it extracts travel records with origin type as "urban villages" and arrival type as "commercial building" in morning peak hours, and travel records with departure type as "commercial building" and arrival area as "urban villages" in evening peak hours. After data cleaning to eliminate the abnormal latitude and longitude of the departure and arrival locations, the effective record of morning peak commute trips was 23,622, and the effective record of evening peak commute trips was 13,083. The bellowing Table 1 shows an example of DiDi travel record.

Table 1. Description of the raw data from DiDi ride-sourcing company.

Data	ID	Origin Longitude	Origin Latitude	Destination Longitude	Destination Latitude	Departure Time	Peak Type	Origin Type	Destination Type	...
1 July 2016	2798439385	113.9832	22.75048	114.0681	22.62849	09:19	1	Urban village	Commercial buildings	...
1 July 2016	2949340043	113.9351	22.54093	113.9609	22.56938	19:43	3	Commercial buildings	Urban village	...
...	...	...	...	...	...	...	...	...	...	

Since departure and arrival types have been limited to "urban village" and "commercial building" during the data preprocessing stage, DiDi travel during the commuting period can reflect the occurrence and attraction of commuting trips and the distribution of employment and residence; the departure during the morning peak (morning origin, MO) and evening peak arrival (evening destination, ED) locations can reflect the distribution of residences (urban villages); and morning peak arrival (morning destination, MD) and evening peak departure (evening origin, EO) locations can reflect the location of the workplace. The distribution of DiDi commuting trips occurring across urban villages during the morning and evening peak hours on the scale of 490 TAZs in Shenzhen is shown in Table 2 and Figures 2–5.

Table 2. Description of DiDi commuting trips.

Travel Frequency	Max.	Min.	Mean	S.D.
MO	1752	1	285.1	264.7
MD	2836	1	271.1	329.0
EO	2338	3	365.9	364.5
ED	2294	3	365.7	365.8

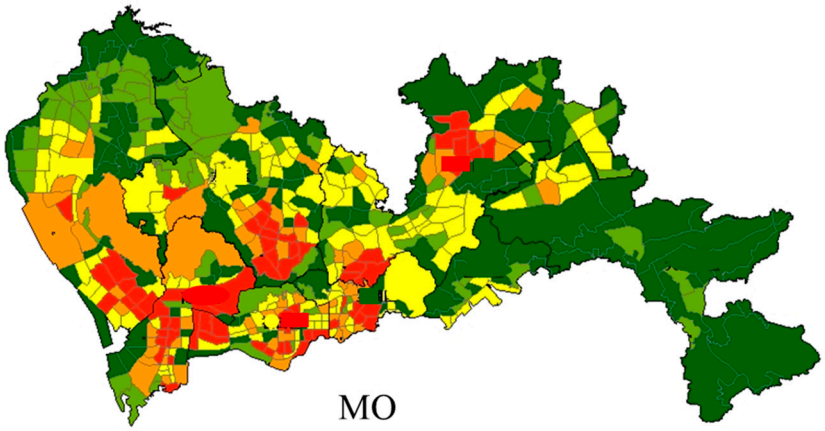


Figure 2. Distribution of DiDi trips during the MO.

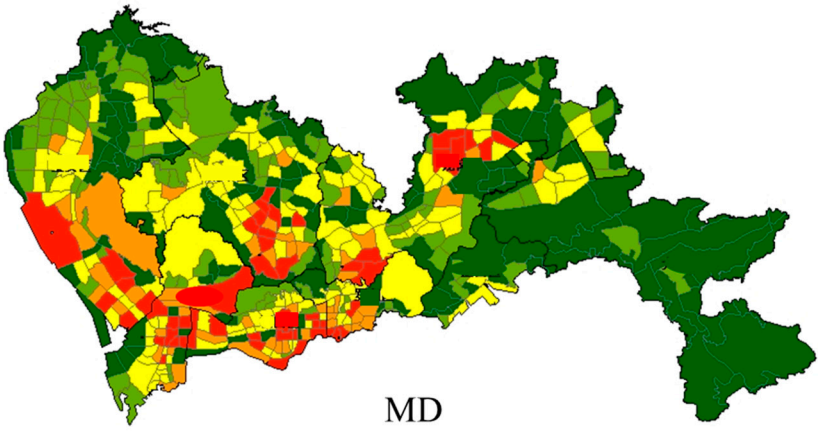


Figure 3. Distribution of DiDi trips during the MD.

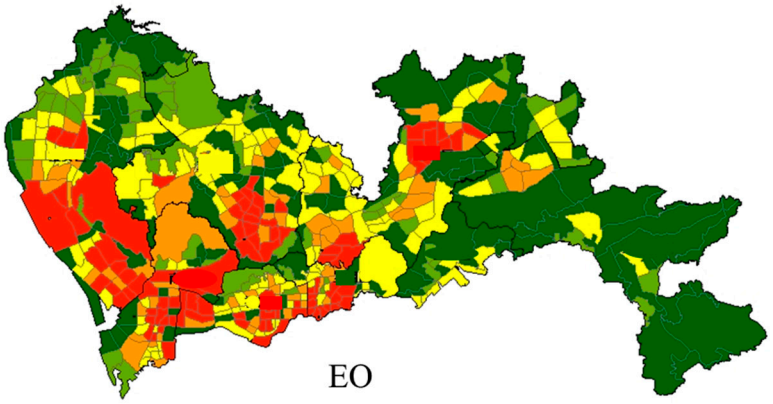


Figure 4. Distribution of DiDi trips during the EO.

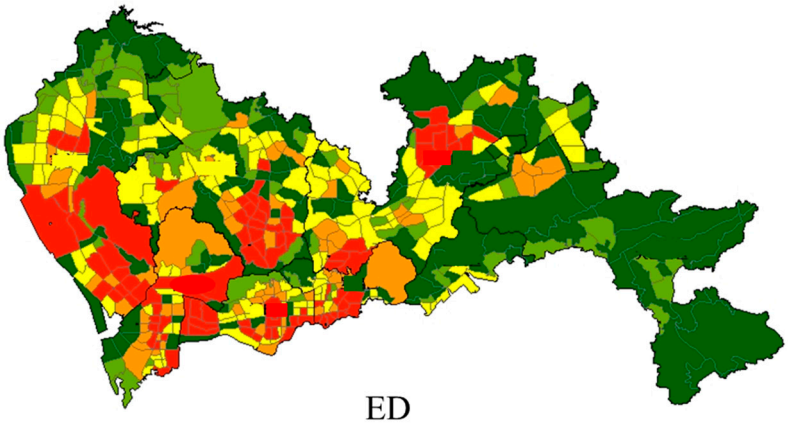


Figure 5. Distribution of DiDi trips during the ED.

From Figures 2–5, DiDi's travel demand shows a certain degree of agglomeration in space, most of which is concentrated in the central and southwestern central areas, which also reflects the agglomeration and distribution of job–housing in Shenzhen. Figures 2–5 and Table 2 also reflect the uneven distribution of DiDi commuting trips within each community. Although both MO and ED can reflect the distribution of residential areas, the agglomeration characteristics of the two are not exactly the same. Moreover, the agglomeration characteristics of MD and EO are not exactly the same, so it is necessary to study the four types of trips separately.

Regarding the variables of the built environment in this section, nine indicators were measured using a TAZ scale, including population density, building density, mixed land use, road network density, percentage of non-motorized lanes, road width, road length, bus line density, and bus stop density. The statistical characteristics of the built environment variables are shown in Table 3.

Table 3. Description of built environmental variables.

Category	Name	Unit	Max.	Min.	Mean	S.D.
Density	Population density	10,000/km^2	8.004	0.003	2.150	1.781
	Building density	m^2/km^2	0.378	0.001	0.201	0.086
Diversity	Mixed land use	Nil	1.891	0.486	1.357	0.227
Design	Road network density	km/km^2	17.282	0.408	7.986	3.173
	% of non-motorized lane	Nil	1.000	0.287	0.799	0.143
	Road width	m	19.871	6.232	11.773	2.222
	Road length	km/km^2	4.011	0.024	0.992	0.693
Public transit	Bus line density	km/km^2	35.069	0	3.599	4.550
	Bus stops density	No./km^2	52.283	0.100	12.936	7.777

3.3. Modeling Spatial Dependence Effect

The spatial correlation can generally be reflected in the following three aspects.

First, when there is a spatial correlation between the dependent variables, the spatial model is expressed by Equation (1), which is called spatial autoregression.

$$\boldsymbol{y} = \lambda \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\varepsilon} \quad (1)$$

Here, $\boldsymbol{W}$ represents the spatial weight matrix, and the commonly used spatial weight matrix is a binary adjacency matrix, which represents the spatial adjacency relationship between TAZs. The built environment variables of each TAZ are used as independent variables. After the independent variables have been introduced, the SAR model equation is shown by Equation (2). That is, the spatial autoregressive model not only explains the

demand for DiDi trips within the built environment of a certain TAZ but also reflects the spatial dependence of the DiDi travel demand among TAZs.

$$\boldsymbol{y} = \lambda \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{2}$$

Second, on the basis of the SAR model, travel demand is not only affected by the built environment variable in the self-TAZ but may also depend on adjacent TAZs. For the built environment variables of the residential area, the spatial Durbin model (SDM) can be constructed, as shown in Equation (3).

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\delta} + \boldsymbol{\varepsilon} \tag{3}$$

Third, the spatial dependence can also be embodied by the error term when the missing variables are not included in the independent variable but have an impact on the dependent variable, which has a spatial correlation, or the unobservable random variable has a spatial correlation. That is, the impact is the unobserved DiDi travel demand within TAZs. A spatial error model (SEM') can be constructed according to Equation (4) as follows:

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\mu} \tag{4}$$

Among them, the generation process of the disturbance term is shown in Equation (5) as follows:

$$\boldsymbol{\mu} = \rho \boldsymbol{W}\boldsymbol{\mu} + \boldsymbol{\varepsilon},\ \boldsymbol{\varepsilon} \sim \mathbf{N}(\mathbf{0}, \sigma^2 \boldsymbol{I}_{\mathbf{n}}) \tag{5}$$

Further, it can be assumed that there is a spatial correlation between the observed and unobserved independent variables. On the basis of SAR, combined with the characteristics of SDM and SEM, the spatial lag and spatial error characteristics were combined to construct multiple spatial correlations to be developed into a new model called the Spatial Durbin Errors Model (SDEM). Previous research has only used a single SDM or SEM' for spatial correlation analysis and did not consider and verify a combination of the two models. The SDEM constructed in this section is shown in Equation (6).

$$\boldsymbol{y} = \lambda \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\delta} + \boldsymbol{\mu} \tag{6}$$

Equation (6) indicates that the DiDi travel demand, built environment independent variables, and unobserved independent variables based on the TAZ are all spatially correlated; that is, the DiDi travel demand of a TAZ is not only affected by the built environment of its own TAZ but is also spatially dependent on other variables within three dimensions: ① The DiDi travel demand of a TAZ is affected by the built environment of urban villages in other TAZs; ② At the same time, there is a spatial interaction between the DiDi travel demand among TAZs; ③ The spatial error term that affects the DiDi travel demand also has spatial dependence.

The SDEM model constructed under the above assumptions was tested by the model applicability test statistics in the next part of this section. If the applicability test passed, it meant that the assumptions of considering multiple spatial correlations were established and the constructed SDEM model was reasonable; if the applicability test failed, the applicability of SDM, SEM', and SAR could be checked in turn.

4. Results

Before performing spatial regression, a multi-collinearity analysis was conducted on independent built environment variables. Variables with a variance expansion factor greater than 5 were removed using a stepwise method. Finally, seven built environment variables were included in the model.

Moran's I test of spatial correlation can reflect the similarity of the unit attribute values in the neighborhoods of the space. If the dependent variable is the observed value of the area, then the Moran's I value of the variable is expressed as Equation (7) as follows:

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(Y_i - \overline{Y})(\overline{Y} - Y_j)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \quad (7)$$

The value of Moran's I statistic is generally between -1 and 1. When the value is smaller than 0, it indicates a negative correlation. When it is equal to 0, it indicates incoherence. When it is greater than 0, it indicates a positive correlation.

Based on the spatial relationship of 490 TAZs in Shenzhen, the software GeoDa 1.20 and Stata 15 were applied to generate a first-order adjacency matrix of the traffic district, reflecting the spatial adjacency relationship of the traffic district, and then the value of Moran's I statistic was obtained, as shown in Figures 6–9.

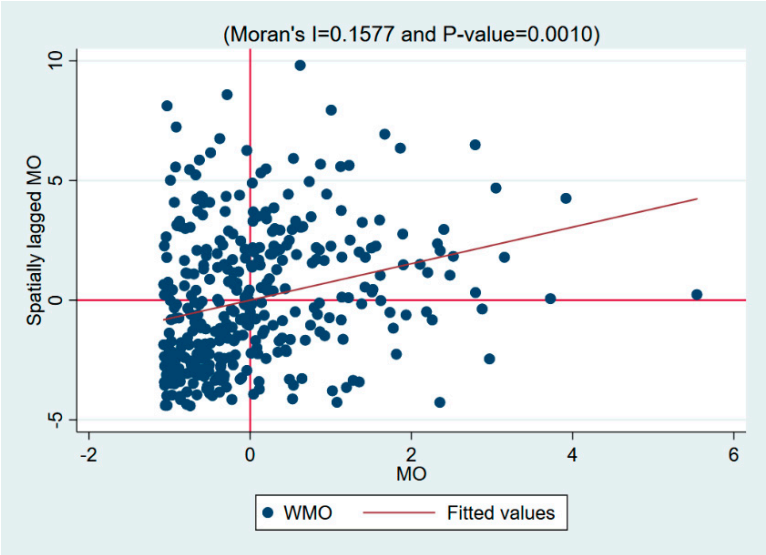


Figure 6. Moran's I statistic for the MO.

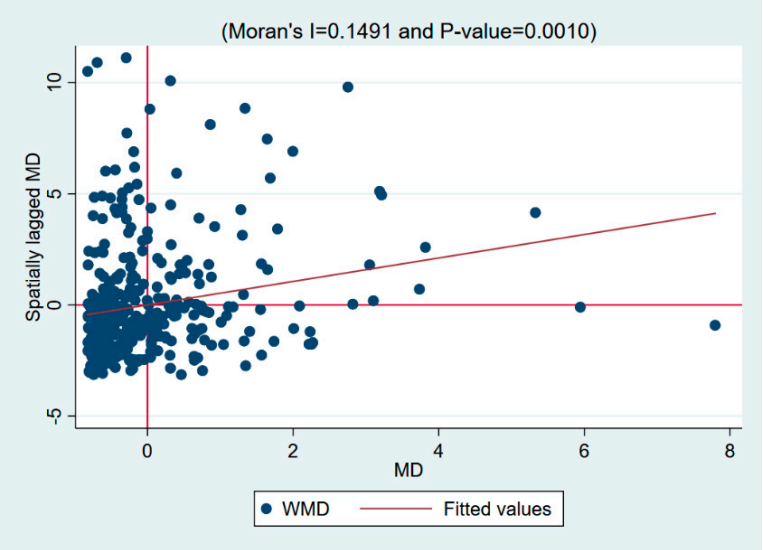


Figure 7. Moran's I statistic for the MD.

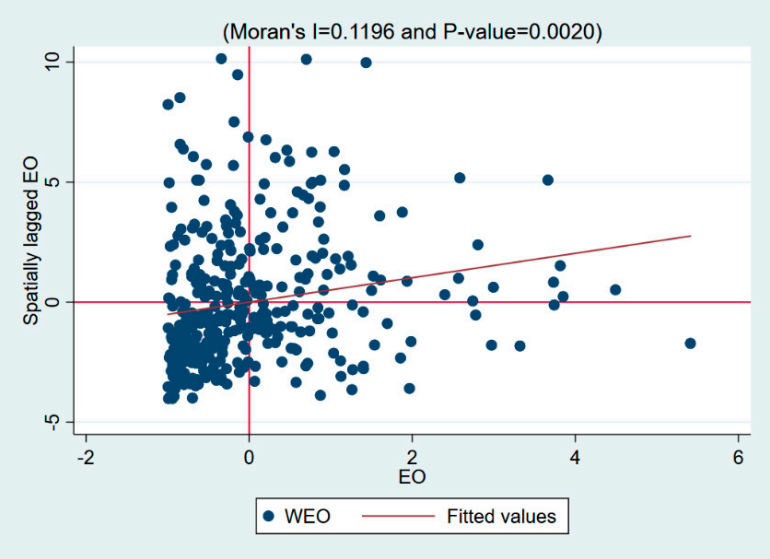


Figure 8. Moran's I statistic for the EO.

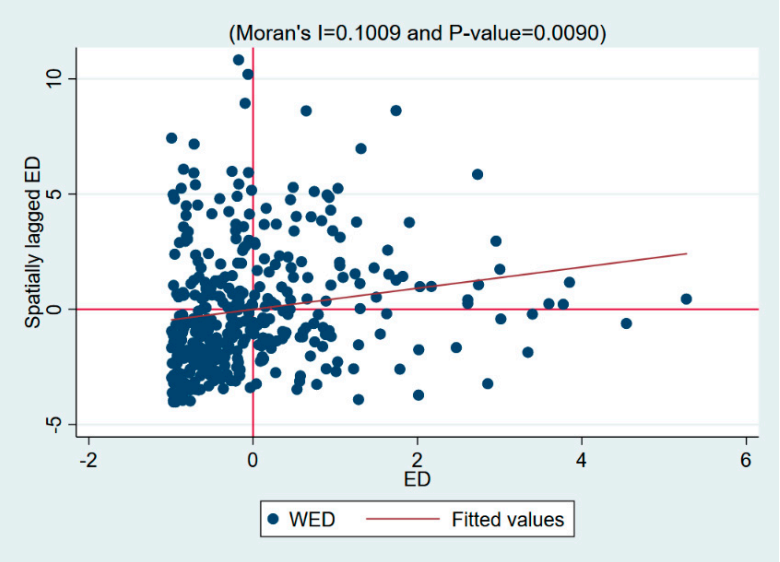


Figure 9. Moran's I statistic for the ED.

From Figures 6–9, it can be seen that the Moran's I statistics of the DiDi travel demand for the MO, MD, EO, and ED within a TAZ were all greater than 0 and passed the 1% significance level test. The results indicate that the spatial distribution of DiDi travel activities was not completely random. In general, its positive spatial correlation characteristics indicate that the characteristics of DiDi travel were similar in space.

The applicability of the SDEM model established in this section was tested, and it was concluded that the test statistics of the Lagrange multiplier (error) and Lagrange multiplier (lag) were very significant (Table 4), from which it can be determined that the spatial Dubin error model of this section was applicable. This means that the dependent variables of the DiDi travel demand based on the geographic unit of the TAZ, the independent variables of the built environment, and the unobserved error variables all had a spatial correlation. Therefore, the explanatory power of the SDEM model in this section was better than that of SAR, which only considered spatial lag. Additionally, it was better than the SDM and SEM models, which only considered spatial error.

Table 4. Application test for the SDEM model.

Index	MO	ED	MD	EO
Lagrange Multiplier (lag)	0.563 **	3.016 ***	5.211 **	0.258 ***
Lagrange Multiplier (error)	3.254 **	0.491 **	7.629 **	4.363 **

** Significant $\alpha = 0.05$; *** Significant $\alpha = 0.01$.

In terms of parameter estimation methods, the generalized method of moments (GMM) was applied because it did not require knowledge of the accurate distribution information of the random error term and allowed for the random error term to have heteroscedasticity and sequence correlation. It was more effective than other parameter estimation methods such as the least-square, maximum likelihood, and instrumental variable methods. The parameter estimation results of the SDEM model are shown in Table 5.

Table 5. Estimation results of the SDEM model.

Variable Index	Variables Name	Urban Villages		Workplace	
		MO	ED	MD	EO
	Constant	−1.562 **	0.638 **	0.913	−2.336 **
X1	Population density	0.391 ***	0.007 **	2.197 **	0.955 *
X2	Building density	0.517 **	0.366 **	0.793 ***	0.955 ***
X3	Mixed land use	−1.327 **	−1.809 **	−2.286 *	−2.674 **
X4	Road network density	0.537	0.183 *	0.097	0.247
X5	% of non-motorized lane	−0.989	−0.721 *	−0.235	−0.699
X6	Bus line density	−0.042 *	−0.448 **	−0.485 **	−0.616 *
X7	Bus stop density	−0.038 ***	−0.091 **	−0.908 ***	−0.209 ***
W_{X1}	W·Population density	−0.708 **	−0.832 **	−0.448 ***	−0.341 **
W_{X2}	W·Building density	−0.903	−0.606	−0.809	−0.396
W_{X3}	W·Mixed land use	0.593 **	0.257 **	0.666 **	0.299 **
W_{X4}	W·Road network	−0.797	−0.753	−0.996	−0.905
W_{X5}	W·% of non-motorized lane	−0.699	−0.081	0.708	−0.255
W_{X6}	W·Bus line density	0.642	0.057	−0.213	0.598
W_{X7}	W·Bus stop density	−0.557 *	−0.812 **	−0.766 *	−0.488 *
/	ρ	0.351 ***	0.296 ***	0.262 ***	0.414 ***
/	R^2	0.796	0.638	0.621	0.665
/	Log likelihood	563.8	601.3	589.1	543.2
/	LR test	463.4	511.5	488.6	426.7

* Significant $\alpha = 0.1$; ** Significant $\alpha = 0.05$; *** Significant $\alpha = 0.01$.

The parameter estimation results corresponding to X1–X7 in Table 5 represent the relationship between the built environment variables of a certain TAZ and the travel demand of the TAZ. For urban village areas, built environment variables basically had the same influence on the MO and ED of online car-hailing commuters. First, population density (X1) and building density (X2) played a significant positive role in promoting the demand for online car-hailing travel, and the variable coefficients were both positive, indicating that the higher the population and building density, the greater the demand for online car-hailing travel. The possible reason was that high density meant more commuting activities and travel demand. Second, mixed land use (X3), bus line density (X6), and bus stop density (X7) had a significant inhibitory effect on online car-hailing commuting trips, and the variable coefficients were all negative, which was consistent with most previous studies. Third, the road network density (X4) and the proportion of non-motorized lanes (X5) had significant negative impacts on the ED. The reason may have been that increasing road network density and the proportion of non-motorized lanes in residential areas promoted non-motorized travel to a certain extent, thereby inhibiting the demand for online car-hailing travel. For the workplace, the impact of built environment variables on the EO and MD of DiDi commuting trips was basically the same as that of urban villages, while the road network density and the proportion of non-motorized lanes did

not show a significant impact; therefore, the number of impact factors in the workplace was even smaller. It is worth noting that the absolute value of the correlation coefficient of a significant influencing factor of the workplace was higher than that of the urban village areas, so the influence of the workplace was greater.

The interaction items of the weight matrix and the built environment variables (W_{X1}–W_{X7}) were spatially lagging variables, and the corresponding parameter estimation results indicate that the DiDi travel demand of a certain TAZ was affected by the space lag effect of the built environment of urban villages. When the coefficient sign of the cross term (W_{X1}–W_{X7}) was consistent with the coefficient sign of the original built environment variable (X1–X7), it indicates that there was a spatial spillover effect; that is, the built environment was positively correlated to the travel demand of the area and the neighboring area. Adversely, it was the spatial competition effect.

From Table 5, population density (W_{X1}), mixed land use (W_{X3}), and bus stop density (W_{X7}) all had significant spatial lag effects. Among them, WX7 manifested as a spatial spillover effect, which means that increasing public transit in a certain TAZ not only suppressed the DiDi travel demand in this TAZ but also reduced DiDi commuting trips in other adjacent TAZs, indicating that the increase in public transport facilities can attract more people from nearby areas to choose public transport instead of an individual motorized travel mode. W_{X1} and W_{X3} show a spatial competition effect; that is, an increase in population density (WX1) in a certain TAZ increased the demand for DiDi travel in this TAZ but led to a decrease in travel demand in other TAZs. In addition, increasing the mixed land use W_{X3}) of a TAZ reduced DiDi commuting trips in the TAZ but increased the demand for DiDi travel in other adjacent urban village TAZs.

5. Discussion and Conclusions

In this study, a Spatial Dubin Error Model was developed to express the spatial dependence effect. The built environmental variables of the urban village and employment were measured based on the geographic unit of TAZ, and the demand for online car-hailing travel was obtained using data from DiDi trips. Two main conclusions were obtained from this study.

(1) The demand for online car-hailing travel is spatially dependent on urban villages and workplaces. The built environment of urban villages and employment areas has basically the same impact on online car-hailing travel. However, overall, the built environment of urban village areas had more factors, and the coefficient of the built environment variable of the employment site was larger in absolute value, indicating that the improvement of the built environment of the employment site had a more significant effect on guiding DiDi travel demand. Built environment factors need to be considered more comprehensively if DiDi travel is guided by urban village areas.

(2) The impact of built environment variables on online car-hailing trips simultaneously showed spatial competition and spillover effects. Since the spatial spillover effect represents a wider range of the impacts of influencing factors when formulating an online car-hailing travel demand management strategy, in order to expand the scope of the influence, the built environment variables (bus stop density) with spatial spillover effects can be adjusted first. Then, the general spatially related variables (building density, bus line network density, road network density, and non-motorized vehicle lane ratio) can be considered. Finally, the variables with spatial competition effects (population density and mixed land use) should be placed at the end.

A reasonable layout of urban villages and employment locations should be paid attention to via reasonable urban renewal strategies. Reasonable thresholds for the proportion of employment positions show be formulated within the radius of suitable walking and non-motorized travel scales around densely populated areas as the lower standard for the planning and construction of employment centers, especially via the construction of large-scale urban complexes in the process of urban village renewal.

Admittedly, due to the limited amount of data obtained, the results of this study may be incomplete. If larger data samples are obtained for repeated tests and verification, the reliability and influence of research results could be improved. Moreover, with a larger sample size, different types of urban villages and regeneration methods could be further studied. Regarding the dynamic renewal of urban villages, they are a temporary informal residence, and their ultimate destination is regeneration, regardless of the time and measures that must be taken. The regeneration of urban villages is a dynamic process. It must not only conform to the blueprint of urban planning but also pay attention to the feasibility of the implementation of regeneration measures. To make the regeneration of urban villages better coordinated with urban development, dynamic renewal strategies deserve attention. Moreover, requirements for the regeneration of urban villages during various stages of urban development may also change. Hence, the regeneration of urban villages must reserve space for future development, make effective use of the flexible role of urban villages within urban development, and deliver transport vitality and land vitality.

Therefore, although the conclusions obtained from this study are applicable to the upgrade of urban villages at the current stage, more influential factors and comprehensive relationships can be considered in the future with the development of urbanization and transportation.

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