




Article

Exploring the Effects of Urban Built Environment on Road Travel Speed Variability with a Spatial Panel Data Model

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Abstract: Road traffic congestion is a common problem in most large cities, and exploring the root causes is essential to alleviate traffic congestion. Travel behavior is closely related to the built environment, and affects road travel speed. This paper investigated the direct effect of built environment on the average travel speed of road traffic. Taxi trajectories were divided into 30 min time slot (48 time slots throughout the day) and matched to the road network to obtain the average travel speed of road segments. The Points of Interest (POIs) in the buffer zone on both sides of the road segment were used to calculate the built environment indicators corresponding to the road segment, and then a spatial panel data model was proposed to assess the influence of the built environment adjacent to the road segment on the average travel speed of the road segment. The results demonstrated that the bus stop density, healthcare service density, sports and leisure service density, and parking entrance and exit density are the key factors that positively affect the average road travel speed. The residential community density and business building density are the key factors that negatively affect the average travel speed. Built environments have spatial correlation and spatial heterogeneity in their influence on the average travel speed of road segments. Findings of this study may provide useful insights for understanding the correlation between road travel speed and built environment, which would have important implications for urban planning and governance, traffic demand forecasting and traffic system optimization.

Keywords: road engineering; traffic congestion; built environment; spatial econometric model; Points of Interest (POI); travel speed; spatio-temporal data



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1. Introduction

Urban roads generally exist in a particular urban built environment with a constant flow of traffic, which has a direct or indirect continuous impact on the performance of the roads [1]. High-grade roads, such as closed elevated roads or expressways in cities, are often not directly linked to the surrounding built environment. Buildings or places in the city need to be connected to the corresponding roads and thus integrated into the urban road network. Urban road grade distribution has the highest proportion of low- and medium-grade roads, which bear diverse functions such as traffic, connection and living services, and thus their connection with the built environment is relatively close [2].

Urban built environment is composed of various buildings and places that have been artificially constructed and modified, and is a combination of land use patterns, transportation systems, and a series of elements related to urban design that can influence the behavior of residents' activities [3]. The built environment differs from the natural environment in that it is a product of human civilization, providing a spatial, temporal, and social context for human activity, and is a combination of elements related to land use, urban design, and transportation systems. A point of interest (POI) is a specific physical location which someone may find interesting. Restaurants, retail stores, and grocery stores

are all examples of points of interest. POI types and densities can characterize the urban vitality of a region, and the functional areas of a city can be identified by POI [4]. Many studies have used POI to calculate built environment indicators [5].

The complex built environment always affects the adjacent road traffic performance, which is most intuitively reflected in the road speed [6]. The different built environment of the road has different road traffic characteristics and, therefore, shows different speed characteristics, the built environment of the adjacent roads in the combined effect of road traffic speed to generate a continuous impact [7]. The poor performance or congestion of the road is related to the surrounding built environment [8], so understanding the correlation between the road traffic performance and the built environment will help to solve the road traffic congestion. In the urban planning stage, a reasonable match between the future regional road network and traffic demand can be achieved by means of reasonable land use planning and density control; in the urban governance stage, road traffic congestion can be alleviated by means of urban function layout optimization, transportation system optimization and infrastructure improvement.

However, the current research on road traffic congestion mainly focuses on the assessment and prediction of traffic performance, but does not go further to establish the correlation between the road traffic performance and the urban space in which the road traffic is located, which means the solution of road traffic congestion cannot be adapted to local conditions. Therefore, this paper conducts a study on the influence of the built environment surrounding the road on the road travel speed. Because the road traffic status has obvious time-varying characteristics, this study divides one day into 48 time slots and establishes a 48-dimensional road segment average travel speed time series. Meanwhile, the road distribution is spatially random and spatially heterogeneous, and this study considers the influence effect of relative spatial location between road segments. Integrating the above factors, this study builds a spatial panel data with NT observations for N road segments and T time slots, and then constructs a spatial panel data model (SPDM) to study the influence of built environment on road travel speed.

The rest of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 introduces a description of the data and study variables. Section 4 presents the research methodologies and model. Section 5 analyzes the results with brief explanation and discusses the whole study. Section 6 draws the conclusions.

2. Literature Review

The built environment affects road traffic status and road travel speed at different levels. At the macro level, the regional traffic status is closely related to the built environment. Pan et al. constructed a geographically weighted regression (GWR) model to analyze the influence of built environment on traffic state index (TSI) of traffic analysis zone (TAZ), and the results showed that the spatial variation of the built environment influence on traffic performance is large, and the public, commercial and residential POIs, the number of bus routes, bus stops, the number of lanes, and average traffic flow significantly influence the traffic analysis zones' traffic performance [1]. At the meso level, the spatial and temporal variation of road congestion is closely related to the built environment surrounding the road. Zhang et al. constructed a spatial autoregressive moving average (SARMA) model based on taxi trajectory data to study the influence of built environment on road traffic congestion, and the results showed that the long-time congested road segments are mainly concentrated in the city center, and road grades, bus stops, commercial sites, ramps, etc. are highly correlated with traffic congestion [8]. At the micro level involving specific roads, the dynamics of congestion on a particular road is significantly influenced by itself and the surrounding built environment. Zhong et al. used an important arterial road in the central city of a megacity as the research case and constructed a GWR model to analyze the correlation between the road characteristics and the surrounding built environment and the travel time of the road. The results of the global model indicated that the percentage of occupied taxis, the distance to the nearest intersection, and the speed limit are positively

correlated with road travel speed, and the number of bus stops and the distance to the nearest school are negatively correlated with road travel speed, but the results of the GWR model indicate that the built environment has significant spatial heterogeneity in its influence on road travel speed, and that the travel speed of subsections is influenced by the built environment with large variability [7].

The built environment affects the status of road traffic and is also one of the deep-seated causes of road traffic congestion. Based on the close relationship between built environment and traffic congestion on adjacent roads, Qin et al. constructed a graph convolutional network model to predict road congestion using built environment indicators, and the model prediction results were consistent with the real road traffic status obtained from the GPS trajectories of taxis with about 85.5% [9]. Li et al. investigated the coordination relationship between built environment and traffic levels, the results show that the distance from the city center and bus stop have the greatest influence on the coordination relationship [10]. Zheng et al. conducted an interesting study in which they predicted adjacent road traffic based on the occupancy rate of a large office building and achieved good results, which indirectly indicates that the built environment affects the traffic status of adjacent roads [11]. Too high or too low a level of land use polycentricity can lead to more congestion and reduce the efficiency of urban roads, while contiguous residential development can help reduce road congestion [12]. A study based on 100 metropolitan areas in the United States shows that over-concentration of employment exacerbates road traffic congestion. In contrast, the most influential tempering effects come from congestion's own self-regulation impact, non-car mode choice behaviors, adequate highway transportation, focused community structures, urban density, and socioeconomic factors [13]. The built environment has moderating effects on road traffic performance. For instance, the improvement of the public bicycle system increases the proportion of cycling and thus indirectly reduces road traffic congestion [14], and the changes in commuting time caused by the built environment [15].

Land use types are closely related to the generation and attraction of traffic trips [16], then they influence the traffic flow of adjacent roads and urban road traffic status [12]. Spatial clustering of land uses was conducted by Bae et al. to analyze the level of service of roads associated with commercial and industrial land uses at different time periods, and it was found that roads associated with commercial land uses were more congested than those associated with industrial land uses [17]. Tian et al. studied the impact of mixed-use developments (MXDs) on traffic based on household travel surveys and geographic information system (GIS) databases and found that smaller MXDs in walkable areas with good transit access generated significant shares of walk, bike, and transit trips and thus also mitigated traffic impacts. High land use mixture also contributed to a reduction in vehicle kilometers traveled [18]. Vice versa, land use types can be identified and classified based on different traffic trip characteristics. Liu et al. classified the study area based on the number and time characteristics of regional taxi pick-ups and drop-offs, and found that the traffic 'source-sink' areas classified according to this corresponded to land use types, indicating that traffic trip characteristics of different land use types had identifiable and significant differences [19]. Pan et al. used taxi trajectory data for land use type differentiation and urban land function identification, and the results showed the high accuracy of this method [20].

The built environment influences travel behavior [21], which in turn affects road traffic performance. The built environment can have an impact on travel demand and travel mode choice, while travel behavior also subconsciously shapes the built environment [22]. A reduction in travel demand means a corresponding reduction in traffic volume, which has positive implications for alleviating road traffic congestion [5]. A well-developed public transportation system will promote residents to choose public transportation [23]. Bus stops and metro stations are important public transport infrastructures in cities, and their layout and level of service are crucial to the attractiveness of public transportation. The more bus stops there are, the higher the probability of commuters traveling by bus and the

lower the probability of commuters traveling by other modes [7]. Improving accessibility to amenities around metro stations can reduce residents' reliance on cars [18], and a well-developed metro system and favorable neighborhoods surrounding metro stations have greater potential to reduce driving and emissions, and alleviate congestion [24]. The higher the density of intersections, roads, population, etc., the lower the likelihood of driving, so it can be assumed that high-density urban development oriented toward non-motorized travel can help reduce travel distances and increase the proportion of trips made by walking, bicycling, and rail transit [25]. The degree of land use mixture, residential density, metro station density, and road density influence travel distance and are negatively related to road traffic emissions [26].

The built environment influences residential car ownership and use and non-motorized travel patterns and thus indirectly affect road traffic flow [27]. Cao et al. based their study on Oslo and Stavanger cities showed that car ownership is lower the closer the residence is to the city center [28], Ding et al. examine the influences of the built environment at both residential and workplace locations on car ownership, they found that built environment characteristics at work locations, particularly bus stop density and employment density, influence household car ownership [29]. Built environment characteristics at work locations are more influential than residential locations on whether or not to use a car for commuting, especially for dual-earner households [30]. Studies based on hundreds of US cities have shown that the higher the population density, the more vehicle miles traveled per capita [31]. Urban built environments are closely related to the distance traveled by residents, and the construction of urban sub-centers has a significant effect on reducing the distance traveled by car [32]. Personal attributes also affect car ownership and use. Shen et al. found that income, job status, and transportation subsidy were positively associated with car ownership and use in a case study of Shanghai [33]. The built environment also has an indirect effect on car use, such as the built environment of workplace and residence is directly related to car fuel consumption [34]. Taxi (including ride-hailing) trips are similar to cars, which are also associated with the built environment [35]. Without considering the spatial heterogeneity of built environment effects, public transportation trips, car ownership, commercial land use, and manufacturer land use promote taxi and ride-hailing trips. Average commuting time is negatively associated with the number of trips made by these two modes [36].

The built environment affects non-motorized modes of travel such as walking and bicycling, which can also indirectly affect road traffic flow. A study based on 96 US cities shows that public bicycles have a significant positive effect on reducing rush-hour congestion and road traffic congestion in large cities [14]. The built environment of the pedestrian departure location is highly correlated with walking, and built environment diversity has the greatest impact on walking choice [37]. Land use mix, access to recreational facilities and street greenery increase walking time for older adults, but the opposite is true for intersection density and access to the metro. Meanwhile, these influencing factors of built environment have noticeable spatial-varying effects on walking time [38]. Bicycle turnover and time-varying demand characteristics varied widely across docked public bicycle stations, with bicycle stations adjacent to public transportation stations, shopping centers, restaurants, schools, and finance having high ridership on both weekdays and weekends, but stations adjacent to office concentration areas having high ridership only on weekdays [39]. Dockless bike-sharing usually serves the initial or last mile of public transportation transfer connections, and suburban areas with dense branch roads and few traffic light intersections are more popular among bike-sharing users [40]. Population density and employment density are the two most significant factors affecting bike-sharing use, and built environment has a nonlinear effect on bike-sharing use [41]. Schoner et al. show that infrastructure such as bike lanes attract cyclists rather than promote the conversion of non-cyclists to cyclists [42]. However, one should also be aware of the spatial heterogeneity of built environment effects on walking and bicycling use, and non-motorized promotion policies should be tailored to local conditions [43].

In summary, the literature review suggests a number of limitations in existing studies of the effects of built environment on the travel speed of adjacent roads. First, the literature focuses on the correlation study between built environment and traffic behavior, and the direct effect of built environment on the travel speed of adjacent roads has not been adequately studied. Second, the coverage of the built environment included in the study is insufficient, and some built environment indicators are not included or included simultaneously with related built environment indicators. Third, the time-varying characteristics of the road traffic status have not been fully considered.

This study contributes to the existing literatures in the following aspects:

1. A spatial panel data model was constructed to explore the potential impacts of the built environment on the travel speed of adjacent roads, and identify the key built environment factors affecting road travel speed;
2. The speed vectors of road segments are constructed in 48 time slots throughout the day to capture the time-varying characteristics of road traffic performance;
3. The study considers both the spatial dependence and spatial heterogeneity of the effects of built environment on the average travel speed of road segments;
4. The findings may provide useful information and guidance for urban planning and transportation system optimization.

3. Data and Variables

3.1. Study Area

The study area of this paper is the central city of Chongqing. As one of the megacities in China, Chongqing is located in the southwest of mainland China, with a central urban area of about 5467 km² and approximately 10.34 million permanent residents in 2020. The central city of Chongqing straddles the Yangtze and Jialing rivers and four major mountain ranges, making it a typical cluster-type mountain city.

3.2. Data

The study data covers taxi trajectory data, POI data, and vector road network data. The road network data is OSM road network data (OpenStreetMap, <https://www.openstreetmap.org>, accessed on June 2019). OpenStreetMap is a free, editable map of the whole world that is being built by volunteers largely from scratch and released with an open-content license. The scope of the road network data is consistent with the study area. The road types included in the road network data are motorway, trunk, primary, secondary, tertiary, etc. Since the study area of this paper is an urban area, motorway and tertiary roads are mainly distributed in suburban and rural areas, so trunk, primary and secondary roads as the research objects. For the sake of understanding, this paper will refer to trunk, primary and secondary road as arterial, collector, and local road, respectively. Road segment was defined as the link between two main intersections [8]. In addition, the speed calculation accuracy is affected by the serious interweaving of vehicles in the shorter segments [44], so the segments with lengths less than 250 m are excluded.

Taxi trajectory data was collected from one of the largest taxi companies in Chongqing for the period of 20~22 May 2019 (Monday to Wednesday). The taxi fleet size is about 3000. The fields of the trajectory data are vehicle number, time, longitude, latitude, instantaneous velocity, direction angle, and occupancy status (0: empty, 1: occupancy), and the time interval of the trajectory data positioning point is 15 s.

This paper is based on ArcGIS platform for matching GPS location points and road network. The matching method is to match the GPS positioning points to the nearest road in the same coordinate system [45]. To ensure the accuracy of the data, the positioning points with an instantaneous velocity greater than 120 km/h and more than 15 m away from the nearest road were deleted [8], and finally, 90.4% of the positioning points were matched to the road.

POI data is collected from Amap (also known as Gaode map, one of the largest Internet map service providers in China), and POI data contains information such as administrative

area, name, longitude, latitude, address, telephone, and classification. The data are cleaned up to remove duplicate and incomplete data records and abnormal values. After the final POI cleaning, 238,090 POI records are obtained with complete and accurate information in 15 types.

3.3. Explained Variables

The explained variable is the average travel speed of the road segment divided into 48 time slots. The average travel speed of the road segment is calculated using taxi trajectory data. First, map matching is performed, i.e., the trajectories are matched to the road network. To highlight the time-varying characteristics of traffic flow, the trajectory data are divided into 48 time slots with 30 min intervals, and then the trajectories of each time slot are matched to the road network separately to calculate the average speed of the road segment.

After map matching, 876 road segments with speed information in 48 time slots are filtered, and the set of time average speed of each road segment is $V\{t_1, t_2, \dots, t_{48}\}$, and the distribution of filtered road segments is shown in Figure 1, which shows that the filtered road segments are mainly located in the built-up area of the central city and the main inter-regional traffic corridors.

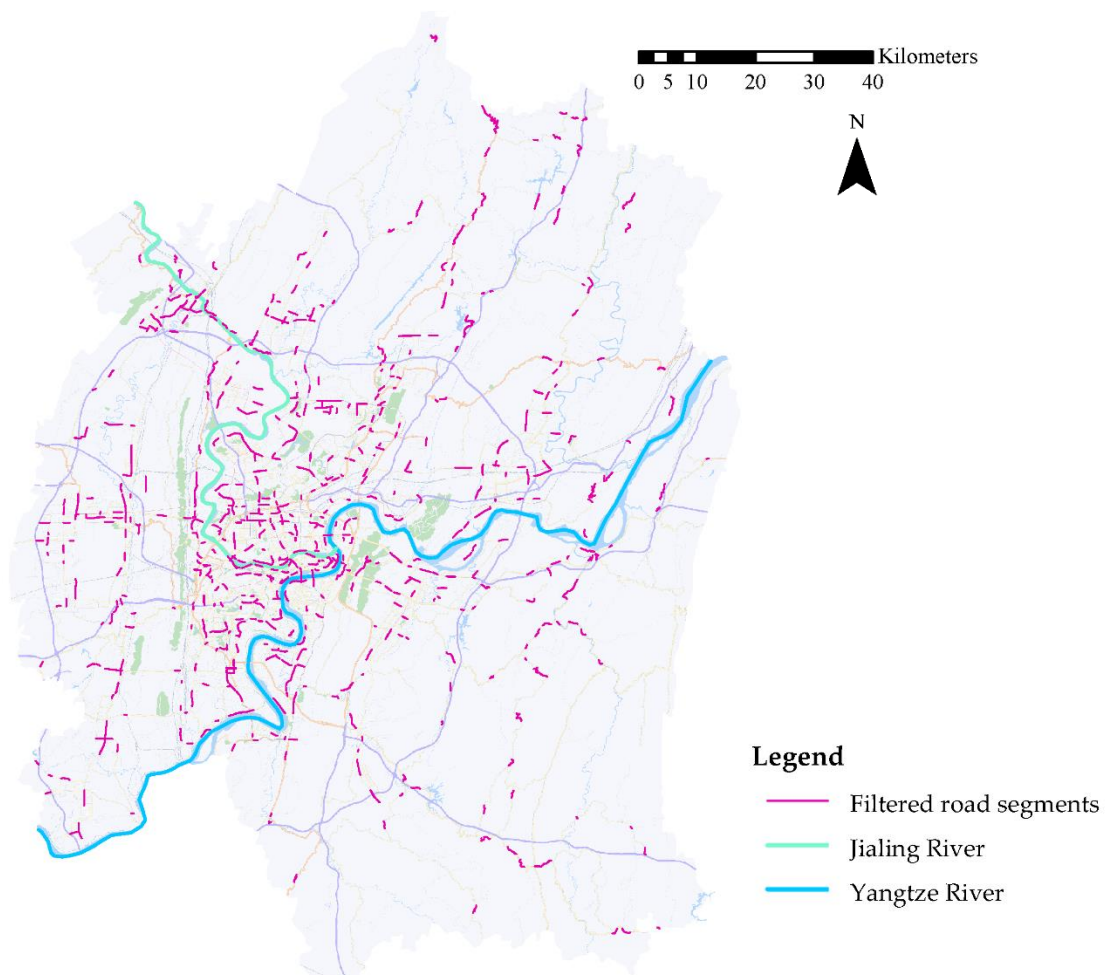


Figure 1. Spatial distribution of filtered road segments.

After obtaining the set of filtered road segments, the average travel speed of 48 time slots for each grade of road segments were calculated, and the speed change trend within one day is shown in Figure 2. The average speed of the road segment in a day fluctuates in

the range of 25 to 45 km/h. There are significant morning and evening peak characteristics of the day; around 8:30 and around 18:30, the average speed is low, and the average speed of the morning peak is lower than the evening peak. The speed of the daytime is significantly lower than the night; around 4:30, the average speed reached the highest value of the day. The average speed is relatively high in the early morning hours, and the aforementioned characteristics are very consistent with the actual traffic status of urban road traffic.

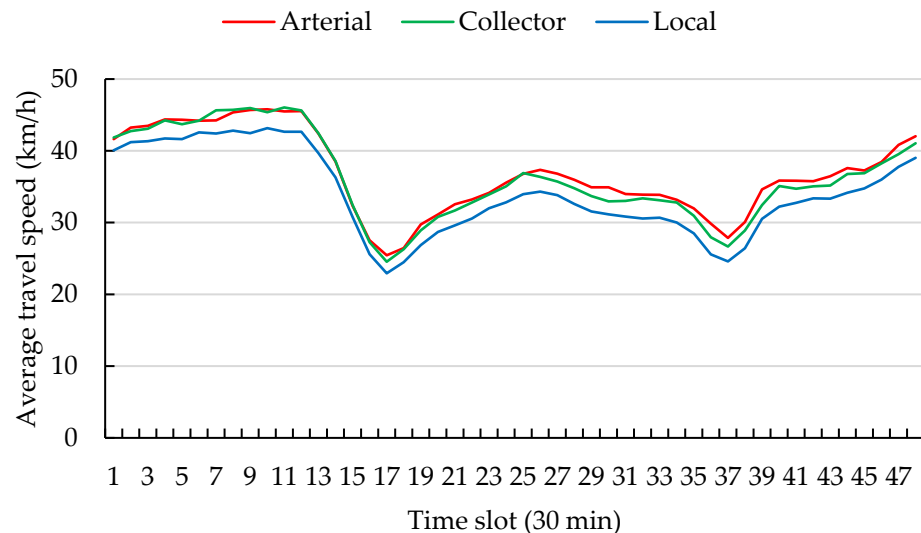


Figure 2. Traffic speed distribution at each time slot by road segment type.

The speed difference of each road segment grade is small, and the overall performance is higher for arterial roads than collector roads and collector roads than local roads. The higher the overall average speed, the greater the speed difference between the various road grades. The average speed difference between arterial roads and collector roads fluctuates around 1 km/h, while the average speed difference between collector roads and local roads fluctuates around 3 km/h. Although the road conditions of arterial roads are relatively better, arterial roads are usually congested due to high traffic flow, which leads to no significant increase in their average speed. In the morning and evening peak hours, all grades of road traffic saturation are high, congestion occurs from time to time, this time the road network travel speed are relatively low. In the late night and early morning hours, there are few vehicles on all grades of roads, and vehicle travel speeds are high. However, due to the large number of urban road intersections, vehicles would be delayed at the intersections and the average travel speed would be lower than the speed limit of the road segment, thus the difference of the average travel speed of the road segments may be less than the difference of the speed limits.

3.4. Explanatory Variables

The explanatory variables are the built environment indicators within the 300 m buffer zone on both sides of the road segment. The built environment indicators are calculated based on POI and OSM road network.

There are 15 types of POIs in the POI dataset. In total, 14 of them are kept unchanged, and the density of the corresponding POIs in the buffer zone of the road segment is calculated. These 14 types of POIs are catering services, scenic spots, companies and enterprises, shopping services, financial and insurance services, scientific culture education, vehicle services, business buildings, living services, sports and leisure services, healthcare services, government agencies and social organizations, accommodation services, residential communities, etc.

The POIs of transportation facilities and services are converted into five types of indicators, namely, metro station (logical type, 0 means there is no metro station in the

buffer zone, 1 means there is at least one metro station in the buffer zone), bus stop density (count/km²), parking entrance and exit density (count/km²), arterial road (logical type, 0 means it is not an arterial road, 1 means it is an arterial road), collector road (logical type, 0 means it is not a collector road, 1 means it is a collector road).

In addition, the POI mixture indicator in the buffer zone of the road segment is calculated. POI mixture is the degree of mix of POI types in the road segment buffer, characterizing the degree of diversity of POI types in the buffer, which is calculated as follows:

$$POIM_i = \begin{cases} \left(\frac{-1}{\ln N_i} \right) \sum_{m=1}^N p_{im} \ln p_{im}, N > 1 \\ 0, N = 0/1 \end{cases}, \quad (1)$$

where $POIM_i$ is the POI mixture of the i th segment buffer, N_i is the number of types of POIs in the i th buffer, and p_{im} is the percentage of the m th type of POIs in the i th buffer to the number of all POIs in the buffer. POI mixture is a dimensionless value, and its value ranges from 0 (homogeneous) to 1 (most mixed), and a larger value indicates a higher mixing degree [46]. In particular, when there is no POI in the buffer or only one type of POI, the mix degree is 0 [47]. In addition, if the number of POIs, metro stations, bus stops, and parking entrances and exits distribution in the buffer is 0 at the same time, the road segment represented by this buffer will be excluded from the study object.

The problem of buffer distance determination on both sides of the road. The service range of the road to the surrounding area differs largely due to differences in urban scale, road function positioning, road network density, land use, geographic environment, population distribution [48], etc. Most literatures used 500 m or 1000 m. The non-linear coefficient of urban roads in mountainous areas tends to be larger, and there are more one-way driving roads. Therefore, on the basis of considering the actual road network in the study area and referring to the relevant literatures, the influence range of the road is determined as 300 m. This distance can ensure the effective coverage of the influence range of the road on the one hand, and on the other hand, it does not produce too much overlapping area [49].

The built environment indicators of the road segment buffer zone are calculated as follows:

1. Establishing a buffer zone with a 300 m range on both sides for all the road segments obtained by filtering;
2. Count the number of various POIs falling into the buffer zone of each road segment separately, and if a POI falls into overlapping buffers, it will be counted repeatedly in several different buffers, respectively;
3. Calculate the various built environment indicators and POI mixture in the buffer zone of each road segment.

The length of the road segment (road length) is also one of the explanatory variables. The descriptive statistics of the 21 explanatory variables are shown in Table 1.

Table 1. Descriptive statistics of the variables.

Variable	Unit	Min	Median	Mean	Max	Std. Dev
Average travel speed	km/h	4.854	31.594	35.699	93.947	16.755
Number of observations	42,048					
Road length	m	250.288	668.845	720.941	3371.352	344.348
Bus stop density	count/km ²	0	0.024	0.035	0.222	0.033
Parking entrance and exit density	count/km ²	0	0	0.050	1.064	0.116
Catering service density	count/km ²	0	0.022	0.216	7.225	0.514
Company and enterprise density	count/km ²	0	0.030	0.094	3.070	0.222
Financial and insurance service density	count/km ²	0	0	0.047	1.308	0.119
Government agency and social organization density	count/km ²	0	0.023	0.104	1.963	0.201
Accommodation service density	count/km ²	0	0	0.058	2.461	0.194

Table 1. Cont.

Variable	Unit	Min	Median	Mean	Max	Std. Dev
Living service density	count/km ²	0	0.036	0.228	8.893	0.561
Healthcare service density	count/km ²	0	0.017	0.097	1.262	0.184
Business building density	count/km ²	0	0	0.015	0.532	0.051
Vehicle service density	count/km ²	0	0.014	0.047	1.431	0.102
Residential community density	count/km ²	0	0.022	0.071	0.675	0.105
Scientific culture education density	count/km ²	0	0.019	0.090	2.036	0.180
Shopping service density	count/km ²	0	0.055	0.493	22.024	1.367
Sports and leisure service density	count/km ²	0	0.015	0.083	3.687	0.210
Scenic spot density	count/km ²	0	0	0.016	0.480	0.043
POI mixture	[0, 1]	0	0.862	0.724	1	0.326
Metro station	0/1	0	0	0.130	1	0.337
Arterial road	0/1	0	1	0.761	1	0.427
Collector road	0/1	0	1	0.670	1	0.470
Number of spatial research units	876					

4. Methodology

4.1. Spatial Weight Matrix

Given that a road is a linear unit, this paper takes the center point of the road segment to construct the spatial weight matrix. Generally, the mutual influence between road segments will gradually become weaker due to the growth of distance, and the influence effect is inversely proportional to the distance, so this study constructs the inverse distance spatial weight matrix based on the centroid of the road segment, which is expressed as follows:

$$\omega_{ij} = 1/d_{ij}, \quad (2)$$

where d_{ij} is the distance between spatial unit i and spatial unit j . The distance between spatial units is commonly used as Euclidean distance, Manhattan distance or Arc distance. The difference between the distances is little in a small area, but the Arc distance is relatively closer to the actual value in the calculation of long distances because of the influence of the shape of the Earth, so we apply the calculation method of Arc distance to calculate the distance between space units. The Arc distance is calculated as follows:

$$d_{ij} = R * \arccos \left[\cos(\Delta Lon) * \sin Lat_{r(i)} * \sin Lat_{r(j)} + \cos Lat_{r(i)} * \cos Lat_{r(j)} \right], \quad (3)$$

where R is the radius of the Earth, $\Delta Lon = Lon_{r(j)} - Lon_{r(i)}$.

4.2. Spatial Panel Data Model

In this paper, a panel data containing 42,048 observations (876 individuals \times 48 time slots) of the average speed of road segments by time slots and buffer built environment was developed by the aforementioned method. The panel data model is thus the preferred model for this study. The panel data model can analyze the characteristics of the data composed of each sample on the time series by using the sample information comprehensively, and it can not only study the different situation among the individuals but also describe the dynamic change characteristics of the individuals. Panel data models are widely used in empirical measurement because of their numerous advantages such as portraying individual heterogeneity, attenuating model colinearity, and increasing degrees of freedom.

However, when the study sample involves some spatial research units, the spatial correlation among the research units cannot be neglected. The explanatory variables in the panel data model only incorporate their factors and do not consider the influencing factors of other related areas. Road traffic has relatively obvious spatial and temporal characteristics, and traffic anomalies at a certain point or local area usually have an impact on the

adjacent roads or areas [50], such as the vehicle queues caused by serious congestion at an important node may cause poor road access or congestion in the adjacent areas. Similarly, because the development of urban commerce or industry has a spatial aggregation effect, driven by the development of the area, the neighboring areas of commerce or industry also developed, that is, the built environment of the area will affect the built environment of the neighboring areas, which will also affect its road traffic status. Therefore, the study of road traffic performance needs to consider the spatial interactions and interactions between the road and its surrounding environment and the adjacent roads and surrounding environment, and the spatial panel data model can consider these spatial interactions.

The spatial panel data model can capture the interaction effects between the explained variables, explanatory variables or error terms while considering the spatial effects. This study focuses on the interaction effect of road traffic performance between neighboring areas and the influence of the neighboring built environment on the road traffic performance of the area, so we construct a spatial panel data model containing the spatial lag term of the explained variables and the spatial autocorrelation error term. The spatial lag term of the explained variables mainly portrays spatial dependence, and the spatial autocorrelation error term mainly portrays spatial heterogeneity [51]. Assuming that N , T and k are the numbers of spatial research units, periods and explanatory variables, respectively, the spatial panel data model containing the spatial lag term of the explained variables and the spatial autocorrelation error term takes the form of:

$$y_{i,t} = \lambda \sum_{j=1}^N w_{i,j} y_{j,t} + a_i + X_{i,t} \beta + \mu_{i,t}, \quad (4)$$

$$\mu_{i,t} = \rho \sum_{j=1}^N w_{i,j} \mu_{j,t} + \varepsilon_{i,t}, \quad (5)$$

where i refers to each individual spatial research units ($N = 876$), t refers to each research period ($T = 48$). $y_{i,t}$ represents the observed value of the explained variable (876×48), $X_{i,t}$ is the row vector of k -dimensional explanatory variables ($876 \times 48 \times k$), $\mu_{i,t}$ is the spatial autocorrelation error term. $\varepsilon_{i,t}$ is the error term with mean 0, variance σ^2 and independent identical distribution. β is the k -dimensional column vector of coefficients to be estimated. λ is the spatial autoregressive coefficient and ρ is the spatial autocorrelation coefficient to be estimated. a_i is the spatial unit individual effect, which denotes the influence factor that does not change over time. $w_{i,j}$ are the elements in the spatial weight matrix W .

5. Results and Discussion

To test whether the fixed-effects model or the random-effects model should be used. The test result is p -value $< 2.2 \times 10^{-16}$, the original hypothesis is rejected and the fixed-effects model is appropriate. Therefore, the spatial panel fixed-effects model was constructed and the results were obtained as shown in Table 2.

The results show that the bus stop density, residential community density, business building density, healthcare service density, sports and leisure service density, and parking entrance and exit density have a greater impact on the travel speed of road segments. The higher the bus stop density in the region, the higher the travel speed of the road segment, indicating that reasonable ground public transport services can improve the regional traffic performance to a certain extent [1,7] and that ground public transport remains important in ensuring the efficiency of urban road traffic performance [52]. The residential community density is negatively correlated with the travel speed of adjacent road segments. The residential area in the central city of Chongqing is dominated by high-rise buildings, and residential communities tend to have high population density and high traffic generation and attraction. At the same time, parking spaces in residential communities are usually difficult to meet the demand, and random on-street parking further affects the efficiency of road traffic adjacent to residential communities [53]. In addition, residential communities

are usually surrounded by a large number of living service stores, which have the potential to interfere with the traffic performance of adjacent roads. Business buildings are similar to residential communities in that they are also places where people and vehicles crowd together, and their adjacent roadway speeds are bound to be affected.

Table 2. Results of Spatial Panel Data fixed-effects Model.

Variable	Estimate	Std. Error	t. Value	Pr (> t)
Road length	0.001	0.0003	5.132	2.865×10^{-7} ***
Bus stop density	48.672	3.602	13.511	$<2.2 \times 10^{-16}$ ***
Parking entrance and exit density	11.344	1.879	6.039	1.550×10^{-9} ***
Catering service density	0.076	0.655	0.116	0.908
Company and enterprise density	0.633	0.994	0.636	0.525
Financial and insurance service density	6.995	2.038	3.432	0.0006 ***
Government agency and social organization density	1.259	0.850	1.481	0.139
Accommodation service density	−7.514	1.200	−6.263	3.787×10^{-10} ***
Living service density	−2.349	0.647	−3.628	0.0003 ***
Healthcare service density	14.727	1.194	12.331	$<2.2 \times 10^{-16}$ ***
Business building density	−21.697	3.583	−6.055	1.401×10^{-9} ***
Vehicle service density	1.388	1.029	1.349	0.177
Residential community density	−38.521	1.638	−23.524	$<2.2 \times 10^{-16}$ ***
Scientific culture education density	4.255	0.987	4.311	1.628×10^{-5} ***
Shopping service density	−0.925	0.174	−5.329	9.858×10^{-8} ***
Sports and leisure service density	11.671	1.391	8.388	$<2.2 \times 10^{-16}$ ***
Scenic spot density	−2.238	2.758	−0.812	0.417
POI mixture	2.428	0.280	8.671	$<2.2 \times 10^{-16}$ ***
Metro station	−0.037	0.284	−0.129	0.897
Arterial road	−2.824	0.231	−12.243	$<2.2 \times 10^{-16}$ ***
Collector road	−2.056	0.208	−9.891	$<2.2 \times 10^{-16}$ ***
ρ	−0.481	0.109	−4.427	9.576×10^{-6} ***
λ	0.173	0.064	2.708	0.007 **

Significance codes: '***' 0.001; '**' 0.01.

Healthcare services have a positive impact on the travel speed of road segments. Large general hospitals usually have a negative impact on the surrounding road traffic [54], but because the healthcare services referred to in this paper include general hospitals, specialty hospitals, clinics, pharmacies, medical checkups and healthcare institutions, etc., the number of these healthcare services other than large general hospitals is larger and more widely distributed, and their traffic impact is much less than that of large general hospitals. The sports and leisure service density and the parking entrance and exit density also have a positive impact on the travel speed. Sports and leisure venues are usually sparsely distributed, and large stadiums generally have sufficient parking resources and few hours to gather a large number of people and vehicles, which attracts and generates little traffic during idle hours and thus does not generate large traffic pressure on the surrounding roads. The high density of parking entrances and exits means that parking resources are abundant and fewer on-street parking and cruising vehicles will improve roadway order and thus reduce traffic disruption [55].

The road segment length has a significant but low effect on the travel speed of the road segment, indicating that the length of the road segment does not significantly affect the travel speed, which may be due to the fact that the length of the road segment less than 250 m has been eliminated during the filtering of the road segment. The presence of a metro station does not have a significant effect on the travel speed of the road segment, indicating that the road traffic is not significantly associated with the metro station. The effect of different road grades on traffic speed is not significant. The effect of POI mixture on travel speed is also small. Other than accommodation services and financial and insurance services, which have some influence on travel speed, the influence of other types of POI density on the travel speed of road segments is relatively small.

The spatial autoregressive coefficient λ is greater than 0 and significant at the 1% significance level, indicating that the traffic speed of adjacent road segments have a positive effect on their speed, and the traffic status of road segments in the region is interrelated, and the spread and dissipation of congestion affects adjacent areas. The spatial error parameter ρ is significant at the 0.1% significance level, indicating that there is spatial heterogeneity between the surrounding built environment of adjacent road segments.

In addition, the presence or absence of spatial effects in the research units was tested by the method proposed by Baltagi et al. [56], with the hypothesis that there is no spatial correlation, i.e., $\lambda = 0$. The test result was p -value $< 2.2 \times 10^{-16}$, and the original hypothesis was rejected, indicating the existence of a spatial correlation between spatial research units. This conclusion is consistent with the conclusion of spatial correlation in the results of the SPDM model.

6. Conclusions

This study explores the relationship between built environment and road traffic status, and constructs a spatial panel data model at the road segment level to examine the effect of urban built environment on the average travel speed of adjacent roads considering the effect of time variation. In this study, taxi trajectories are divided into 30 min time slots and then matched to road segments to calculate the average travel speed of road segments. The road segments with speed information available for 48 time slots throughout the day in the central city of Chongqing, including arterial roads, collector roads and local roads, were selected. After that, a 300 m buffer zone was established on both sides of the filtered road segments, and the built environment indicators in the buffer zone were calculated for each road segment. The built environment indicators are calculated based on POI.

The set of road segments obtained by filtering shows more core urban areas and less suburban areas in spatial distribution. The average travel speed of the three grades of road segments by time shows significant characteristics of morning and evening peaks, but the average travel speed of the evening peak is slightly higher than that of the morning peak. The higher the grade of the road segment, the higher its average travel speed, but the difference is not large, especially since the average travel speed of arterial roads and collector roads are very close. The 30 min time slot division method can reflect the time-varying characteristics of the average travel speed of road segments in more detail.

There is a large variability in the effect of built environment on the average travel speed of the roadway. Bus stop density, residential community density, and business building density are the key factors affecting roadway speed, and bus stop density has the maximum and positive effect, while residential community density and business building density have a negative effect. The influence of healthcare service density, sports and leisure service density, and parking entrance and exit density is also significant, and they are all positive effects. The influence of road segment attributes such as grade and length on the average travel speed is small. The effects of built environment on road travel speed have significant spatial correlation and spatial heterogeneity.

Results of the study reveal the correlation between the built environment and the adjacent road traffic performance, providing information and guidance for urban planning and transportation system optimization. There are significant differences in the degree of influence of various built environment types on adjacent roadway performance, as well as differences in the degree of influence of different functional types of built environment. The positive impact of bus stops on the travel speed of road segments indicates that high coverage of public transport services does help to improve adjacent road traffic performance, which is also consistent with the findings of related literature [1,7] and, therefore, the allocation of ground transit should be emphasized in both the planning and transportation optimization stages of cities. There are differences in the effects of the built environment on travel speed between residential and workplace, and thus the supply and management of transportation should be treated differently.

In closing, this research could be extended in several directions. First, the road segments of different grades are studied separately. Different grades of roads have different functional positioning, their closeness to the surrounding built environment, and traffic flow characteristics, and thus the correlation between the built environment and the road segments may have variability. Second, the socioeconomic indicators within the buffer zone of the road segment, such as demographic characteristics, income, and education, are considered, because they are highly correlated with car ownership [29] and car use [32], and residents' travel mode choice [57]. Third, the clustering of road segments based on road segment built environment indicators, and the study of different clusters of road segment built environment indicators and the variability of built environment indicators on road segment travel speed, so as to analyze the matching of road planning function positioning with the status quo function and provide guidance for road optimization.

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