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Weighted Centrality and Retail Store Locations in Beijing, China: A Temporal Perspective from Dynamic Public Transport Flow Networks

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Abstract: The spatial relationship between transport networks and retail store locations is an important topic in studies related to commercial activities. Much effort has been made to study physical street networks, but they are seldom empirically discussed with considerations of transport flow networks from a temporal perspective. By using Beijing's bus and subway smart card data (SCD) and point of interest (POI) data, this study examined the location patterns of various retail stores and their daily dynamic relationships with three weighted centrality indices in the networks of public transport flows: degree, betweenness, and closeness. The results indicate that most types of retail stores are highly correlated with weighted centrality indices. For the network constructed by total public transport flows in the week, supermarkets, convenience stores, electronics stores, and specialty stores had the highest weighted degree value. By contrast, building material stores and shopping malls had the weighted closeness and weighted betweenness values, respectively. From a temporal perspective, most retail types' largest correlations on weekdays occurred during the after-work period of 19:00 to 21:00. On weekends, shopping malls and electronics stores changed their favorite periods to the daytime, while specialty stores favored the daytime on both weekdays and weekends. In general, the higher store type level of the shopping malls correlates more to weighted closeness or betweenness, and the lower-level store type of convenience stores correlates more to weighted degree. This study provides a temporal analysis that surpasses previous studies on street centrality and can help with urban commercial planning.

Keywords: complex network; POI; smart card data; public transport flows; KDE; weighted centrality

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1. Introduction

Location is a key factor for the commercial success of retail stores, as consumers tend to patronize stores that have higher access advantages [1,2]. The configuration of a city's transport network has been found to have significant impacts on the distribution of retail service activities [3–7]. Additionally, in urban planning and design, the locations of retail services are important for city growth and vitality [8]. Therefore, location analysis of retail stores is important for retail investment decisions and urban planning.

Location analysis has been increasingly applied to the retail sector with the growing computing power and the advent of big data [9]. While many location-allocation models have been developed and used for location decision making of retail stores [10,11], identifying the spatial pattern of retail locations is still an important and basic research task to date. Generally, many factors may affect the location retail stores, which made it a complex and multi-dimensional problem [12]. Among these factors, transportation is often regarded as a key element for retail locations. There is much empirical literature focusing on exploring the spatial relationships between physical street networks and retail stores. Various accessibility indices are optional to capture the convenience of retail stores in physical street networks [13,14]. Among them, the centrality features of a store are critical for the commercial competition of market areas according to the central place theory and spatial interaction theory [15]. Based on the approaches of space syntax or complex networks, the centrality features of a transport network can be measured by various centrality indices [16]. The multiple centrality assessment (MCA) model, which groups several indices together, has been applied to examine the relationship between street centrality and the spatial distributions of retail stores [17]. Different cities around the world have been examined, and the findings indicate that the centralities of the physical street network may well explain the retail distributions [18–21]. The study of Wang and Chen et al. [22] first examined the differences among location preferences for different types of retail stores. Later, new data sources as point of interest (POI) data were introduced [23]. As the relationship between various types of stores and multiple centrality indices of street networks across regions and cities were examined, it was revealed that different store types may correlate to different spatial networks centralities [23,24], which is helpful for retail location selection and planning.

While these previous studies have focused on examining the physical street network, few quantitative empirical studies have examined centrality in networks with transport flows. However, the location advantage of attracting transport flows is one important factor that influences the location selection of commercial services. The transport flows can reflect where people would like to go, and the correlation for retail stores is an important element for commercial development. According to the classic Hotelling model [25], the location strategy serves to obtain maximum flows, which are not necessarily geometric central points in space [26]. In addition, the flow network has a temporal attribute. Exploring temporal dynamics in flow networks may provide some possible insights into retail location patterns [27], as temporal factors such as store opening hours and individuals' travel time cannot be addressed by the static location analyses on the physical street network [28,29].

For retail location, it was recognized early that accessibility by public transport is a key issue for a store [30]. Several studies have verified that public transport has a substantial impact on retail patterns in city centers when compared to those of out-of-town malls [31–34]. In the big data era, public transport flow data become available from a smart card system and a number of studies have devised various weighted centrality indices to analyze the complex network of transport flows [35–37]. However, to the best of our knowledge, research on the relationships between retail store locations and their centrality in public transport flow network still lacking.

This paper aims to examine the relationship between weighted centrality indices and various retail stores from a temporal perspective. Beijing is chosen as the case city, in which public transport is well-developed. According to the 2020 Beijing transport development annual report released by the Beijing Transport Institute (http://www.bjtrc.org.cn/, accessed on 10 August 2021), the modal shares of public transport (bus and subway) in most urbanized areas of Beijing are more than 31%, which is greater than that of car and taxi (about 22% and 2.5%). In our study, the public transport flows are extracted from the bus and subway smart card data (SCD) of Beijing. The remainder of this study is organized as follows. Section 2 describes the study area and data preparation, and discusses the research methods. Section 3 presents the results. The last section discusses and summarizes the main findings.

2. Materials and Methods

2.1. Study Area and Data Preparation

Beijing is the capital of China and includes both urban and rural areas. As this study addresses public transport flows and retail activity, the analysis is conducted in the urban area of Beijing. Here, an area of approximately 38.64 km^2 within the sixth ring road of Beijing is selected as the case study area. The area covers most urbanized areas of Beijing.

The study area is divided into grid cells to conduct further analysis. The appropriate cell size of the study units may affect the results and computational complexity. In previous studies of retail stores and network centralities, a cell size of 1 km × 1 km has most commonly been used despite some variances [21]. Considering the road network density, this study selects a cell size of 1 km × 1 km (see Figure 1).

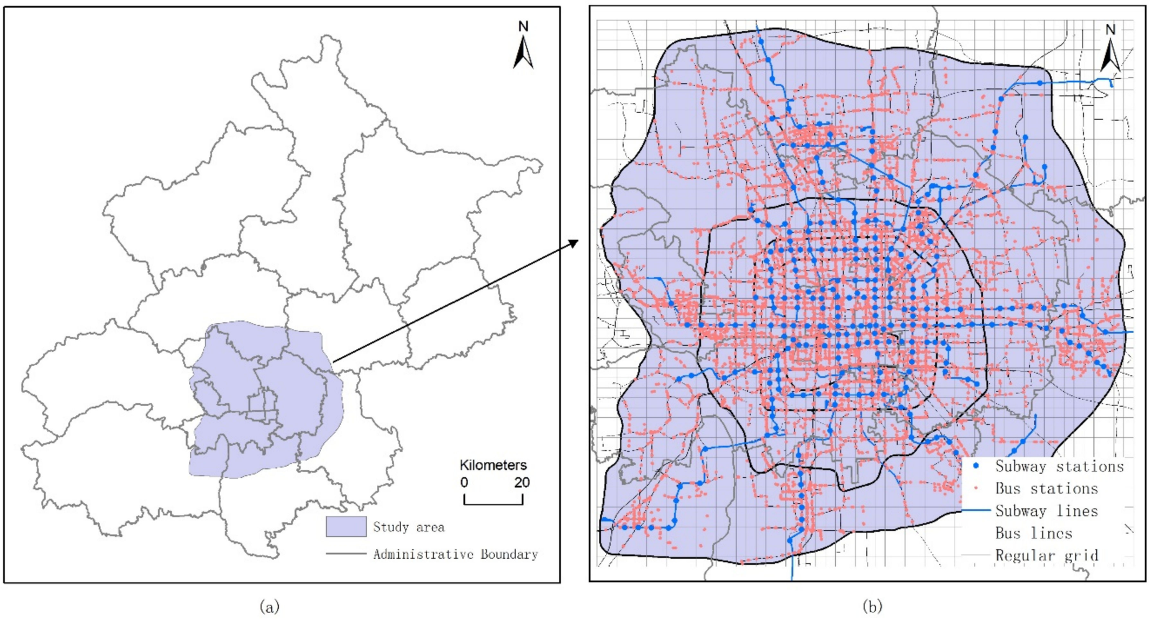

Figure 1. Case study area: (**a**) Beijing; (**b**) sixth ring road of Beijing.

Point of interest (POI) data are used to construct a dataset of retail stores. The POI data for 2018 are sourced from Autonavi (Gaode), which is a popular electronic navigation map in China that provides information on the names, location, and types of various retail stores. Based on previous studies and the classification of POI data [21,23,37], 72 subtypes of retail stores (as illustrated in Table 1) were extracted from the POI dataset. According to the Retail Type Categorization of China (RTCC), they were categorized within six major categories, including shopping malls, supermarkets, convenience stores, specialty stores, electronics stores, and building material stores. A total of 91,243 POI retail stores in Beijing were extracted. The distributions of the six types of POI are shown in Figure 2.

Table 1. Categories and total counts of POI.

Category	Sub-Category	Total Counts
Shopping malls	Shopping Plaza, Shopping Center, etc.	768
Supermarkets	Carrefour, Wal-Mart, Hualian, Watsons, etc.	12,756
Convenience stores	7-ELEVEN, Circle K, etc.	15,027
Specialty stores	Sports Store, Clothing Store, Franchise Store, Personal Care Items Shop, etc.	27,222
Electronics stores	Home Electronics Hypermarket, Digital Electronics, Mobile Handsets Sales, etc.	7894
Building material stores	Furniture Store, Kitchen Supply, Hardware Store, Lighting, Porcelain Market, etc.	27,576

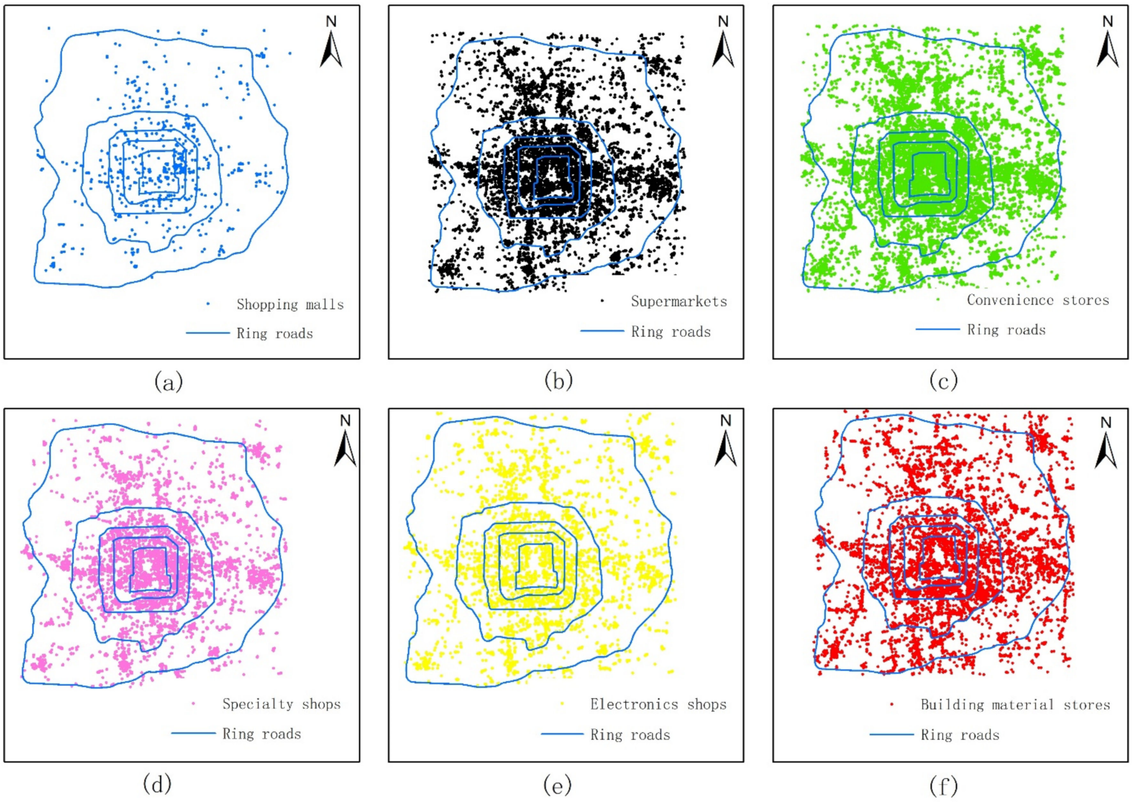

Figure 2. The POI distributions of six types of retail stores: (**a**) shopping malls; (**b**) supermarkets; (**c**) convenience stores; (**d**) specialty stores; (**e**) electronics stores; (**f**) building material stores.

According to the Beijing Statistical Yearbook in 2018, the public transport lines of Beijing sum to a total length of 19,881 km, including 637 km of metro lines. The annual passenger volume of public transport is 7038.18 million, which includes 3848.43 million metro passengers. Approximately 565 bus lines and 22 subway lines pass through the case study area, and there are more than 3000 bus stations and 259 subway stations within the sixth ring road of Beijing. Approximately 7.5 million bus and 2.5 million subway cards swipes are recorded each day. The modal shares of public transport in the urbanized areas of Beijing are more than 30%.

The public transit flow data used in this study were obtained from one week of bus and subway smart card data (SCD) from 19 April to 25 April 2015, which were obtained from the Beijing Public Transport Group. In recent years, two big events have serious impacts on public transit in Beijing. In 2014, Beijing started a price reform on its public transport system and adjusted public transportation fares to a higher level since then. Another event happened in 2019: the transport flows were much impacted by COVID-19. Therefore, the year 2015 may well reflect the stage of post-era of price reform and pre-era of COVID-19. We processed the data in two steps. First, the total flow for one week was accumulated by time periods of one day to capture temporal changes in transit flow. Various divisions of time periods have been used to aggregate the datasets in previous studies [38–40]. Considering the purpose of analysis and data features, the dataset was organized into seven periods based on two-hour intervals from 7:00 to 21:00 in the day. Then, we separated the weekly data according to weekdays and weekends to detect the differences in public traffic flow between working days and rest days. Sample records and selected fields of smart card data are shown in Table 2. All flow data were accumulated on the above-mentioned raster grid with a cell size of 1 km × 1 km and were based on 7 time periods. The aggregation process was completed in Python.

Table 2. Sample records of smart card data.

Time	Card Number	Type	Line Number	Vehicle Number	Boarding Station	Departure Station
20150813091012	46,343,397	1	751	95,740	17	11
20150813112013	80,245,649	1	609	83,601	5	8

2.2. Research Methods

In this paper, the SCDs of buses and subways are used to construct a network of public transport flows, and then, a weighted MCA model is used to calculate centralities for multiple time slices. The kernel density estimation (KDE) method is used to transform the centrality indices and the distribution of different types of retail stores to the same data framework.

Constructing a network is the basis for further complex network analysis. In this study, a weighted complex network is established according to public transport flows in the study area. Each raster grid is abstracted as a network node, and then, the transport flows between nodes are used as the weights of edges between nodes. The generated complex network has the topological characteristics of P-space, as all stops along a route can be connected if there is one line connecting two nodes [41].

2.2.1. Multiple Weighted Centrality Assessment Indices

Centrality indices provide a common and effective approach to analyze the spatial configurations of transport networks [42]. For a flow network, weighted complex indices have been developed and applied to public transport [43–45]. We select three critical indices in the MCA model to measure the characteristics of centrality: namely, weighted degree, weighted betweenness, and weighted closeness. These measures were computed by using the "networkx" package in Python [46].

Equation (1): weighted node degree centrality (WNDC). The unweighted degree is a basic indicator that is defined as the number of nodes that are connected to the focal node [47]. In a weighted network, WNDC is generally defined as the sum of weights and labeled as node strengths [48]. In this study, WNDC is defined as the traffic flow between network nodes on the constructed complex network that directly flows in or out of a node, which is formalized as follows:

$$\mathrm{WNDC}_{\mathrm{i}}^{\mathrm{w}} = \sum_{\mathrm{j}\in \mathrm{v(i)}} \mathrm{w_{ij}} \tag{1}$$

where $\mathrm{w_{ij}}$ represents the traffic flows between nodes i and j. Here, the WNDC value of node i is the total volume of the passenger O-D flows connected with node i.

Equation (2): weighted node betweenness degree (WNBC). The original indicator of betweenness refers to how often a node is traversed by the shortest paths connecting all pairs of nodes in the network [47]. In a weighted network, it has been suggested that the reciprocal link weights should be used to define the shortest path in a weighted graph, which reflects the ability to transmit through the chain or indicates whether a node is included in a path with a relatively large flow [49]. Here, the WNBC is adopted, which can be formalized as follows:

$$\mathrm{WNBC}_{\mathrm{i}}^{\mathrm{w}} = \sum\nolimits_{\mathrm{k}\neq \mathrm{i}\neq \mathrm{j}\in \mathrm{N}} \frac{\delta_{\mathrm{kj}}(\mathrm{i})}{\delta_{\mathrm{kj}}} \tag{2}$$

where δ_{kj} is the number of shortest paths between nodes j and k and $\delta_{\mathrm{kj}}(\mathrm{i})$ is the number of these shortest paths through node i.

Equation (3): weighted node closeness centrality (WNCC). The original indicator of closeness is the average distance from a given starting node to all other nodes in the network [50]. It measures how close a node is to all other nodes along the shortest paths of the network. In a weighted network, WNCC considers both the number of intermediary nodes and the tie weights [51], which are defined as:

$$\mathrm{WNCC}_{\mathrm{i}}^{\mathrm{w}} = \frac{\mathrm{n}-1}{\sum_{\mathrm{j}\in \mathrm{v(i)}} \mathrm{d_{ij}}} \quad (3)$$

where n is the total number of nodes in the network. $\mathrm{d_{ij}}$ is the shortest distance between nodes i and j. In a public transport flow network, $\mathrm{d_{ij}}$ is the minimum number of nodes to pass between nodes i and j. The weight in this case is defined in the same manner as that in the weighted betweenness.

2.2.2. Using KDE to Convert Density Values to a Grid Frame

The KDE method is used to convert the density values of retail stores and multiple centrality values to the same raster data frame to further perform correlation analysis. The advantage of KDE is that the density values at the middle locations of the raster grid are generated by considering the surrounding events [52,53]. For points that fall within the search range, different weights are assigned. The closer the point to the search center, the greater the weight, and vice versa. Equation (4) for estimating the kernel density at point x at the center of a grid is as follows:

$$\hat{f}(\mathrm{x}) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (4)$$

where K is the kernel function, h is the bandwidth, and n is the total number of points within the bandwidth. In this study, the grid cell size is set at 1 km × 1 km, and a bandwidth is set at 5 km. The KDE tool in ArcGIS was used to obtain the density values.

3. Results

3.1. Distribution Characteristic of Retail Stores

Figure 3 shows the spatial distribution characteristics of the KDE values of six types of retail stores. The values are graded into five classes in the sub-figures, and the method of natural breaks is applied, which minimizes the sum of variance within the groups. A general pattern of higher values in the core area and lower values in the peripheral areas can be observed. Among the densities of the six types of retail stores, building material stores have the largest average density, which is followed by specialty stores, convenience stores, supermarkets, electronics stores, and shopping malls. For the high-density centers, building material stores, specialty stores, supermarkets, and electronics stores had multiple centers. Shopping malls and convenience stores showed a strong monocentric pattern.

3.2. Distribution Characteristics of Weighted Centrality

Figure 4 shows the spatial distributions of three weighted centrality indices: namely, weighted degree, weighted betweenness, and weighted closeness, based on the network constructed by the total public transport flows in the week. The lighter the color, the lower the centrality value. The degree values gradually decrease from the core to peripheral areas, and high values are mainly distributed within the fourth ring road. Betweenness presents a pattern with a high-value core and multiple secondary centers. The high-value core of the closeness is mainly distributed between the second east ring road and fourth east ring road. The closeness also exhibits a decreasing trend from the core to the peripheral areas, and the area with a high value covers a wider range.

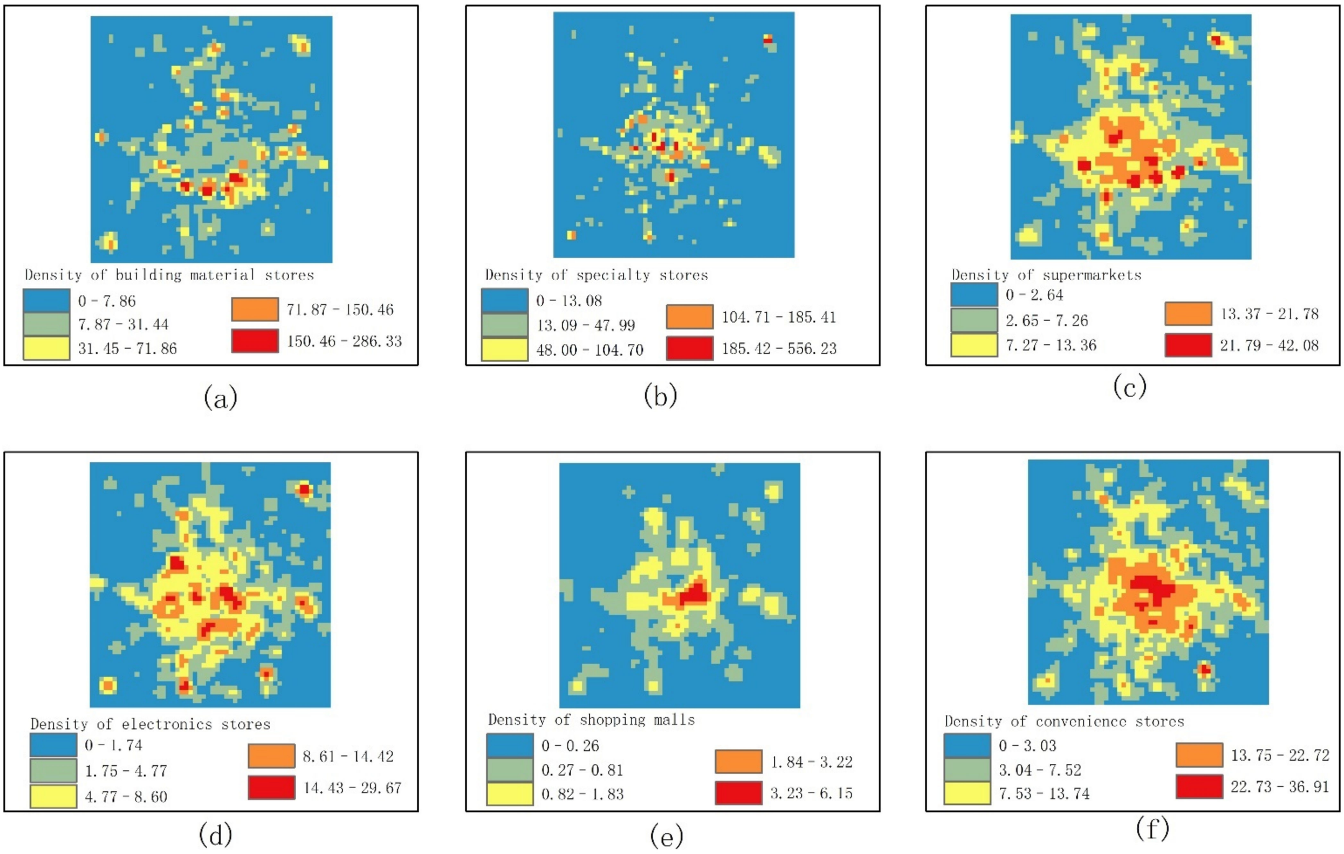

Figure 3. Density distributions of different types of retail stores determined by KDE: (**a**) building material stores; (**b**) specialty stores; (**c**) supermarkets; (**d**) electronics stores; (**e**) shopping malls; (**f**) convenience stores.

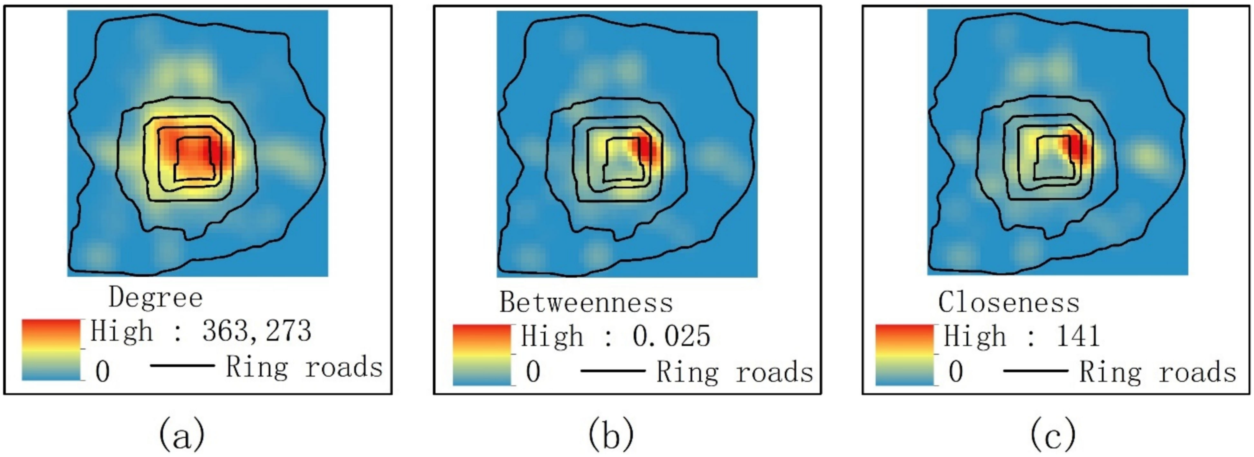

Figure 4. Spatial distributions of three weighted centrality indices of the total flow network: (**a**) degree; (**b**) betweenness; (**c**) closeness.

Figure 5 shows the temporal changes in the average values of the three weighted centrality indices on weekends and on weekdays. The horizontal axis represents time, and the points on the graph correspond to the median values of the different time periods.

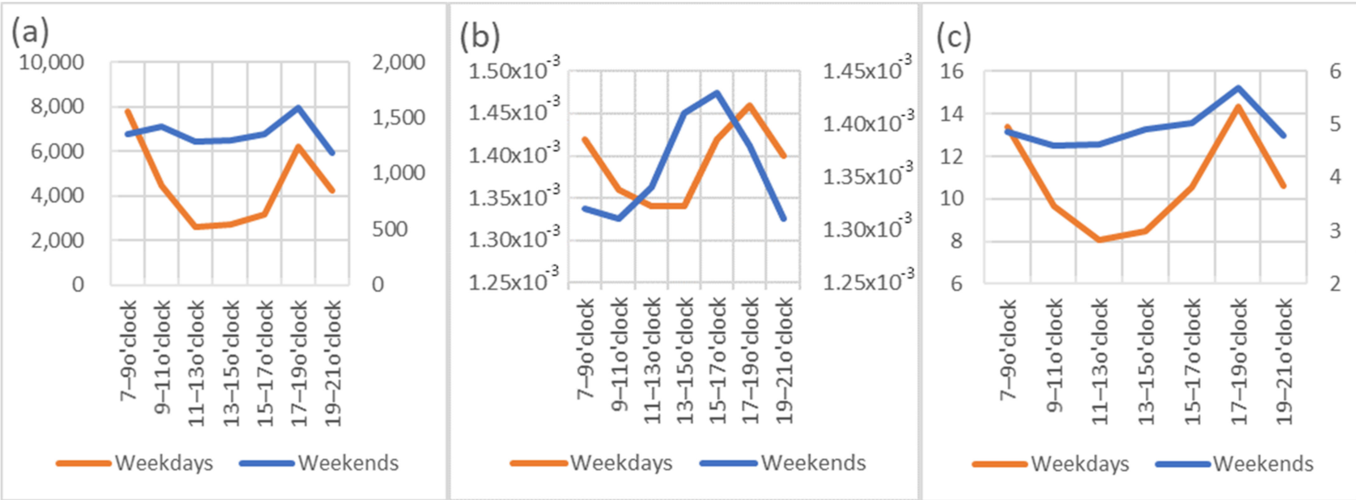

Figure 5. Temporal variations of the three weighted centrality indices on weekdays and weekends: (**a**) degree; (**b**) betweenness; (**c**) closeness.

The vertical axis represents the centrality values. Overall, three indices show quite different temporal patterns. For weekdays, the degree curve shows two peaks, which indicate a morning peak from 7:00 to 9:00 and an evening peak from 17:00 to 19:00, and the value of the early peak is greater than that of the late peak. The betweenness and closeness curve also show two peaks, but the late peak is greater than the early peak. The low point of three indices appeared at 11:00–13:00, and an extra low point appeared at 13:00–15:00 for betweenness.

Compared with weekdays, the weighted degree curve for weekends fluctuates mildly before 17:00. The peak appeared at 17:00–19:00 and then the low point appeared at 19:00–21:00. For betweenness, the curve of weighted betweenness for weekends shows a trend of high in the middle and low on both sides. The peak appeared at 15:00–17:00, which is earlier than the time of the evening peak for weekdays (17:00–19:00). Compared with weekdays, the range of fluctuation for the weighted closeness curve for weekends is smaller. The peak appeared at 17:00–19:00.

The spatial distributions of weighted centrality indices in seven periods of a day from 7:00 to 21:00 are calculated, and here, we present three of them, including the morning period from 7:00 to 9:00, noon period from 11:00 to 13:00, and after-work period from 19:00 to 21:00.

Figure 6 shows the spatial distributions on weekdays. In general, the core area of Beijing maintains an advantageous position in the networks with public transit flow. Although the distributions exhibit certain similarities for different time periods for the same index, there are some differences. The degree centrality values between the west second ring and west third ring road change with time, with a trend of increasing first and then decreasing. For betweenness, the two secondary centers between the west second ring road and west third ring road and the south second ring road and south third ring road change over time, with a trend of increasing first and then decreasing. The other sub-centers also exhibit minor changes with time. For closeness, peripheral areas change slightly with time, and the central area also exhibits minor changes with time. Figure 7 shows the spatial distributions on weekends. Compared with weekdays, the weighted centrality values change relatively smoothly over the weekends.

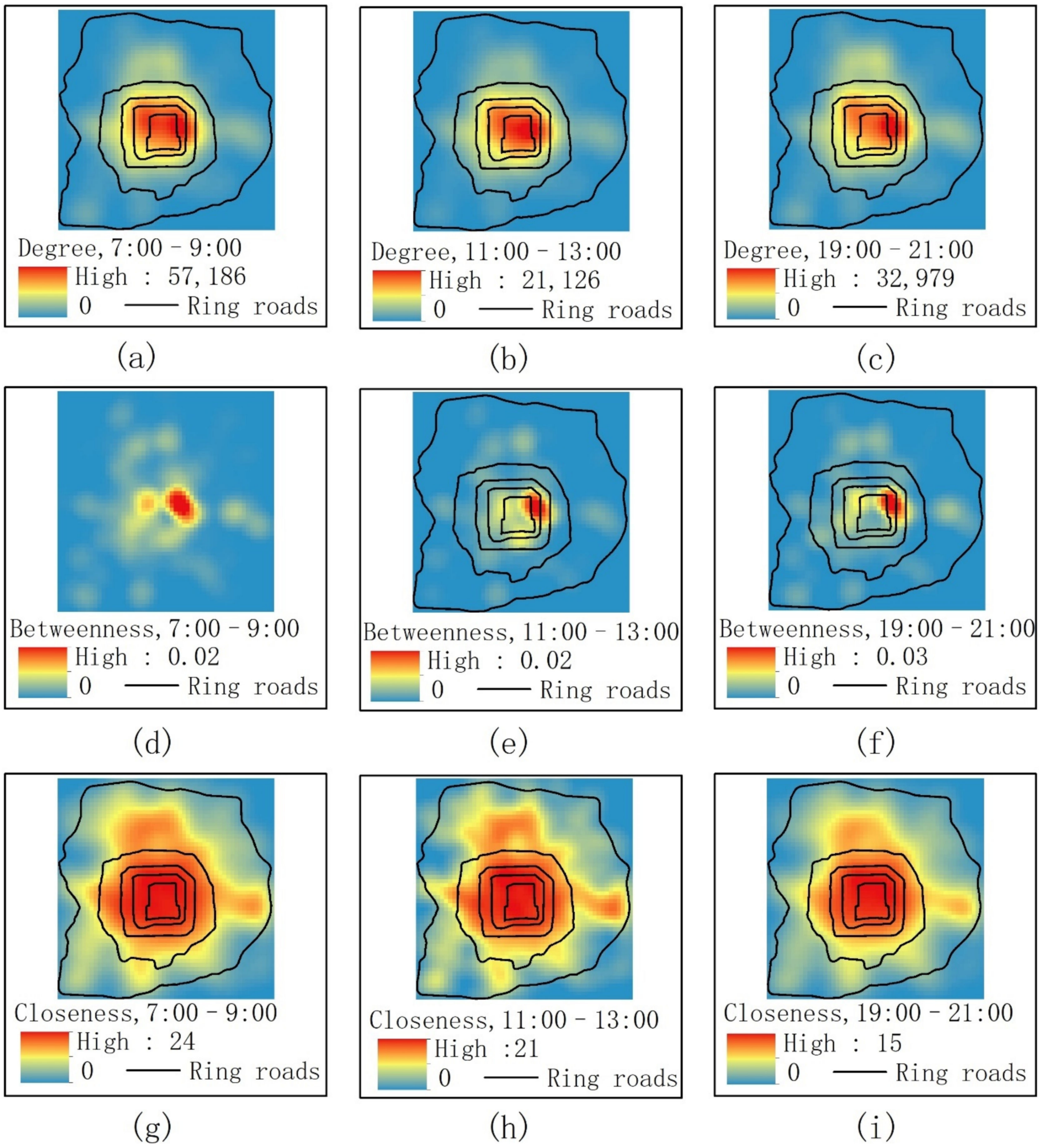

Figure 6. Spatial distributions of weighted degree centrality indices on weekdays: (**a**) degree, 7:00–9:00; (**b**) degree, 11:00–13:00; (**c**) degree, 19:00–21:00; (**d**) betweenness, 7:00–9:00; (**e**) betweenness, 11:00–13:00; (**f**) betweenness, 19:00–21:00; (**g**) closeness, 7:00–9:00; (**h**) closeness, 11:00–13:00; (**i**) closeness, 19:00–21:00.

3.3. Relationships between Retail Store Locations and Weighted Centrality from a Temporal Perspective

This section examines how the density distribution of retail stores may correlate with the weighted centrality indices. First, the flow network without temporal division is examined, which is constructed by the total public transit flows of the whole week. Table 3 shows the highest correlation coefficients between various retail stores and weighted centrality indices. Pearson's correlation analysis was conducted between the density of retail stores and weighted centrality indices.

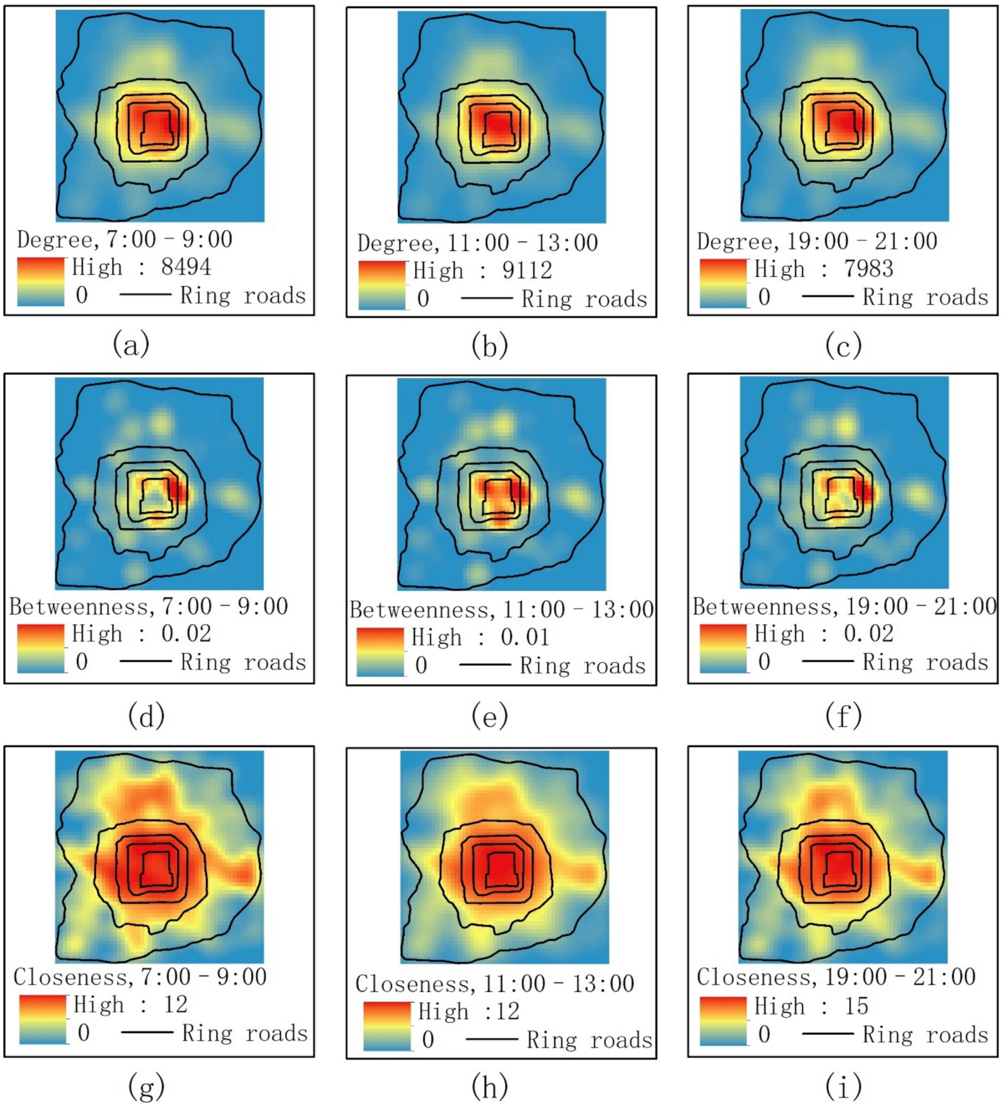

Figure 7. Spatial distributions of weighted degree centrality indices on weekends: (**a**) degree, 7:00–9:00; (**b**) degree, 11:00–13:00; (**c**) degree, 19:00–21:00; (**d**) betweenness, 7:00–9:00; (**e**) betweenness, 11:00–13:00; (**f**) betweenness, 19:00–21:00; (**g**) closeness, 7:00–9:00; (**h**) closeness, 11:00–13:00; (**i**) closeness, 19:00–21:00.

Table 3. Correlation coefficients of KDE values of stores and weighted centrality indices of total flow network.

Retail Types	Degree	Betweenness	Closeness
Shopping malls	0.770	0.785	0.580
Supermarkets	0.722	0.625	0.718
Convenience stores	0.812	0.747	0.740
Electronics stores	0.716	0.636	0.685
Specialty stores	0.553	0.485	0.413
Building material stores	0.261	0.211	0.371

First, most store types have rather high correlation coefficients with weighted centrality indices. Convenience stores, shopping malls, supermarkets, and electronics stores have strong correlations with all weighted centrality indices, with coefficients above 0.6. The highest correlation coefficients for each type of store are more than 0.7, and the highest coefficient is achieved by convenience stores (with values above 0.8). Specialty stores have the highest coefficient, exceeding 0.5. Only building material stores exhibit weak correlations with weighted centrality indices (the highest coefficient is less than 0.4), which is consistent with the previous findings by using street centrality indices [22–24], which implies that building material stores may be relatively less correlated to the public transport flow. These results indicate that most of the six types of retail stores are highly correlated to weighted centralities in the public transport flow network.

Second, four types, namely, supermarkets, convenience stores, electronics stores, and specialty stores, show the highest correlations with weighted degree. Only shopping malls show the highest correlation coefficients with weighted betweenness, with the highest correlation coefficient value reaching 0.785. This finding indicates that high-grade retail stores prefer nodes that are included in paths with relatively large flows. In comparison, it has been reported that betweenness performs well in previous physical street network studies [18,22–24]. This is also consistent with our findings, as betweenness in street networks reflects the frequency of the shortest paths passing through, while the weighted degree in this study directly reflects public traffic volume. The results indicate that transport volume has a significant impact on the location patterns of retail stores.

Then, the flow networks for different periods of a day with a distinction between weekdays and weekends are examined. Tables 4–6 show the temporal analysis results. Tables 4 and 5 show the correlation coefficients to the three weighted centrality indices across store types at different periods, and Table 6 shows the highest correlation coefficients for each store type across the periods of a day and the relative centrality indices. Tables 4 and 5 indicate that correlation coefficients vary across the day. For the relationship between weighted closeness and most retail stores on weekends, there is a continuous slight upward trend in the correlation coefficients with time. The relationships between the weighted degree and building material stores on weekdays are high in the morning and evening and low at noon. However, for the weighted degrees among specialty stores on weekdays, this pattern is reversed.

Table 4. Correlation coefficients of KDE values of stores and weighted centrality indices for each period on weekdays.

Centrality	Retail Types	7:00–9:00	9:00–11:00	11:00–13:00	13:00–15:00	15:00–17:00	17:00–19:00	19:00–21:00
degree	Shopping mall	0.763	0.786	0.775	0.772	0.768	0.768	0.784
	Supermarket	0.723	0.711	0.717	0.714	0.718	0.717	0.718
	Convenience store	0.807	0.810	0.812	0.809	0.809	0.808	0.812
	Specialty store	0.545	0.546	0.562	0.563	0.561	0.552	0.538
	Electronics store	0.715	0.711	0.710	0.708	0.709	0.710	0.721
	Building material store	0.266	0.253	0.252	0.248	0.253	0.257	0.264
betweenness	Shopping mall	0.771	0.786	0.814	0.811	0.815	0.754	0.775
	Supermarket	0.643	0.615	0.637	0.635	0.648	0.572	0.605
	Convenience store	0.751	0.738	0.762	0.763	0.774	0.710	0.724
	Specialty store	0.473	0.460	0.506	0.511	0.515	0.443	0.453
	Electronics store	0.638	0.620	0.650	0.643	0.656	0.581	0.618
	Building material store	0.222	0.215	0.215	0.208	0.220	0.177	0.204
closeness	Shopping mall	0.570	0.589	0.611	0.616	0.628	0.622	0.640
	Supermarket	0.715	0.727	0.741	0.744	0.748	0.742	0.750
	Convenience store	0.733	0.749	0.766	0.770	0.776	0.769	0.783
	Specialty store	0.406	0.420	0.439	0.443	0.454	0.444	0.455
	Electronics store	0.680	0.691	0.704	0.708	0.713	0.709	0.718
	Building material store	0.373	0.372	0.369	0.371	0.368	0.371	0.368

Table 5. Correlation coefficients of KDE values of stores and weighted centrality indices for each period on weekends.

Centrality	Retail Types	7:00–9:00	9:00–11:00	11:00–13:00	13:00–15:00	15:00–17:00	17:00–19:00	19:00–21:00
degree	Shopping mall	0.747	0.747	0.742	0.747	0.750	0.750	0.763
	Supermarket	0.749	0.733	0.724	0.719	0.720	0.727	0.734
	Convenience store	0.817	0.811	0.806	0.805	0.806	0.810	0.820
	Specialty store	0.540	0.554	0.559	0.563	0.564	0.557	0.550
	Electronics store	0.733	0.717	0.712	0.709	0.709	0.719	0.727
	Building material store	0.294	0.270	0.260	0.253	0.253	0.266	0.277

Table 5. *Cont.*

Centrality	Retail Types	7:00–9:00	9:00–11:00	11:00–13:00	13:00–15:00	15:00–17:00	17:00–19:00	19:00–21:00
betweenness	Shopping mall	0.752	0.758	0.769	0.753	0.729	0.766	0.769
	Supermarket	0.688	0.694	0.703	0.655	0.639	0.667	0.694
	Convenience store	0.765	0.776	0.790	0.754	0.734	0.770	0.777
	Specialty store	0.486	0.504	0.556	0.587	0.581	0.564	0.519
	Electronics store	0.672	0.677	0.685	0.644	0.630	0.657	0.683
	Building material store	0.266	0.267	0.266	0.220	0.213	0.226	0.256
closeness	Shopping mall	0.577	0.588	0.601	0.610	0.622	0.624	0.640
	Supermarket	0.726	0.728	0.735	0.740	0.744	0.744	0.752
	Convenience store	0.745	0.749	0.758	0.764	0.770	0.771	0.783
	Specialty store	0.413	0.423	0.433	0.441	0.451	0.451	0.460
	Electronics store	0.688	0.691	0.699	0.704	0.710	0.711	0.719
	Building material store	0.375	0.368	0.367	0.366	0.364	0.366	0.366

Table 6. Highest correlation coefficients of all periods.

Store Types	Weekdays			Weekends		
	Period	Centrality	Coefficient	Period	Centrality	Coefficient
Shopping malls	19:00–21:00	Betweenness	0.815	11:00–13:00	Betweenness	0.769
Supermarkets	19:00–21:00	Closeness	0.750	19:00–21:00	Closeness	0.752
Convenience stores	19:00–21:00	Degree	0.812	19:00–21:00	Degree	0.820
Specialty stores	11:00–13:00	Degree	0.563	13:00–15:00	Betweenness	0.587
Electronics stores	19:00–21:00	Degree	0.721	7:00–9:00	Degree	0.733
Building material stores	7:00–9:00	Closeness	0.373	7:00–9:00	Closeness	0.375

Table 6 shows that most of the highest correlation coefficients are rather large both on weekends and on weekdays. Compared with the results for the total flow network (Table 3), the values of the highest correlation coefficients here are larger, which means that analyses without time divisions may underestimate correlations. For the same store types, most types, except for shopping malls, have higher correlations on weekends. Most types show consistency in a preference for the highest centrality index from weekdays to weekends. Only the index type of specialty stores changes in degree on weekdays to betweenness on weekends, but its correlations are less than 0.7.

It is noteworthy that the three types of shopping malls, supermarkets, and convenience stores sell general commodities but differ in store size and diversity in their commodity types. For these three types, they all nearly achieve the highest correlations during the period of 19:00–21:00 for the whole week, while the only outlier is that the shopping mall type correlates more strongly to a different period of 11:00–13:00 on weekends. The same period implies that most consumers go shopping after work, but shopping behavior for malls on weekends may differ, as people may like to spend time in malls.

Another interesting result for the three types is that the highest centrality indices are different: convenience stores correlate best with degree, supermarkets correlate best with closeness, and shopping malls correlate best with betweenness. Recall that for the total flow network without periods in Table 3, the highest centrality index for the supermarket changed here from degree to closeness. In this case, the results of the total flow network may be misleading. Moreover, recall that the degree reflects the total traffic flow, the closeness reflects the closeness to all nodes in the flow network, and the betweenness reflects the traffic corridor. Thus, it can be inferred that the higher levels of store types are associated with higher correlations to the key structure of the flow network.

For the two types of specialty stores and electronics stores, both correlate best to degree centrality on weekdays, and neither correlate best with the period of 19:00–21:00 on weekends. These results imply that people may visit these types of stores after work on weekdays and may visit them at various periods in the daytime on weekends.

4. Discussion and Conclusions

This paper examines the relationships between the spatial distributions of six types of retail stores and their weighted centrality indices in the public transport flow network from the perspective of temporal dynamics. Three weighted node centrality indices were measured, e.g., degree, betweenness, and closeness. This study contributes to existing research on static physical street networks by analyzing the traffic flows of networks and their dynamic time processes.

The findings illustrate that generally, the distribution patterns of six types of retail stores are influenced by weighted street centrality significantly. Except for building material stores, all types of stores are highly correlated with weighted centrality indices. Among the three weighted centrality indicators, weighted degree is the best for four types of retail stores in terms of correlation coefficients and is followed by closeness and betweenness.

Temporal analysis can reveal more details and allow an inference of consumer behaviors. The correlation coefficients at different periods on weekdays and weekends vary over the time of day. For shopping malls, supermarkets, and convenience stores, the highest correlation coefficients on weekdays occur during the after-work period of 19:00 to 21:00. These may change on weekends for shopping malls, as shopping malls provide more than shopping services. Lower store levels correlate to degree centrality, that is, traffic volume itself, such as convenience stores and electronics stores. Higher store levels are correlated with the spatial characteristics of the flow network, such as closeness or betweenness. For specialty stores and electronics stores, people may visit these types of stores after work on weekdays and visit them at various times of the day on weekends.

This research provides a more comprehensive understanding of retail location analysis from a static physical street network to a dynamic flow network. Further research can be conducted to examine the following topics. As consumers may travel in a variety of traffic modes, the flow network that is based on various travel modes is needed to more comprehensively describe traffic flow information. In addition, there is a significant characteristic of disparity of centrality in different cities. Thus, it is necessary to identify the differences among different cities by conducting more case studies.

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References

1. Taneja, S. Technology moves in Chain store age. *GeoJournal* **1999**, *75*, 136–138.
2. Roig-Tierno, N.; Baviera-Puig, A.; Buitrago-Vera, J.; Mas-Verdú, F. The retail site location decision process using GIS and the analytical hierarchy process. *Appl. Geogr.* **2013**, *40*, 191–198. [CrossRef]
3. Hillier, B.; Penn, A.; Hanson, J.; Grajewski, T.; Xu, J. Natural movement: Or, configuration and attraction in urban pedestrian movement. *Environ. Plan. B* **1993**, *20*, 29–66. [CrossRef]
4. Wang, F.; Guldmann, J.M. Simulating urban population density with a gravity-based model. *Socio-Econ. Plan. Sci.* **1996**, *30*, 245–256. [CrossRef]
5. Liu, Y.; Wang, H.; Jiao, L.; Liu, Y.; He, J.; Ai, T. Road centrality and landscape spatial patterns in Wuhan Metropolitan Area, China. *Chin. Geogr. Sci.* **2015**, *25*, 511–522. [CrossRef]

6. Nilsson, I.M.; Smirnov, O.A. Measuring the effect of transportation infrastructure on retail firm co-location patterns. *J. Transp. Geogr.* **2016**, *51*, 110–118. [CrossRef]
7. Rui, Y.; Yang, Z.; Qian, T.; Shoaib, K.; Nan, X.; Wang, J. Network-constrained and category-based point pattern analysis for Suguo retail stores in Nanjing, China. *Int. J. Geogr. Inf. Sci.* **2016**, *30*, 186–199. [CrossRef]
8. Glaeser, E.L.; Kolko, J.; Saiz, A. Consumer city. *J. Econ. Geogr.* **2001**, *1*, 27–50. [CrossRef]
9. Hernández, T.; Bennison, D. The art and science of retail location decisions. *Int. J. Retail Distrib. Manag.* **2000**, *28*, 357–367. [CrossRef]
10. Laporte, G.; Nickel, S.; Gama, F. *Introduction to Location Science*; Springer International Publishing: New York, NY, USA, 2015.
11. Jensen, P. Network-based predictions of retail store commercial categories and optimal locations. *Phys. Rev. E* **2006**, *74*, 035101. [CrossRef]
12. Sánchez-Saiz, R.M.; Ahedo, V.; Santos, J.I.; Gómez, S.; Galán, J.M. Identification of robust retailing location patterns with complex network approaches. *Complex Intell. Syst.* **2021**, *6*, 465.
13. Hansen, W. How accessibility shapes land use. *J. Am. Inst. Plan.* **1959**, *25*, 73–76. [CrossRef]
14. Luo, W.; Wang, F. Measures of spatial accessibility to healthcare in a GIS environment: Synthesis and a case study in Chicago region. *Environ. Plan. B Plan. Des.* **2003**, *30*, 865–884. [CrossRef]
15. Dawson, J.A. *Retail Geography*; Halsted Press: New York, NY, USA, 2013.
16. Casetti, E. Spatial analysis: Perspectives and prospects. *Urban Geogr.* **1993**, *14*, 526–537. [CrossRef]
17. Porta, S.; Crucitti, P.; Latora, V. The network analysis of urban streets: A dual approach. *Phys. A Stat. Mech. Appl.* **2006**, *369*, 853–866. [CrossRef]
18. Porta, S.; Strano, E.; Iacoviello, V.; Messora, R.; Latora, V.; Cardillo, A.; Wang, F.; Scellato, S. Street centrality and densities of retail and services in Bologna, Italy. *Environ. Plan. B Plan. Des.* **2009**, *36*, 450–465. [CrossRef]
19. Omer, I.; Goldblatt, R. Spatial patterns of retail activity and street network structure in new and traditional Israeli cities. *Urban Geogr.* **2016**, *37*, 629–649. [CrossRef]
20. Wang, S.; Xu, G.; Guo, Q. Street centralities and land use intensities based on points of interest (poi) in Shenzhen, China. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 425. [CrossRef]
21. Li, Q.; Zhou, S.; Wen, P. The relationship between centrality and land use patterns: Empirical evidence from five Chinese metropolises. *Comput. Environ. Urban Syst.* **2019**, *78*, 101356. [CrossRef]
22. Wang, F.; Chen, C.; Xiu, C.; Zhang, P. Location analysis of retail stores in Changchun, China: A street centrality perspective. *Cities* **2014**, *41*, 54–63. [CrossRef]
23. Lin, G.; Chen, X.; Liang, Y. The location of retail stores and street centrality in Guangzhou, China. *Appl. Geogr.* **2018**, *100*, 12–20. [CrossRef]
24. Han, Z.; Cui, C.; Miao, C.; Wang, H.; Chen, X. Identifying spatial patterns of retail stores in road network structure. *Sustainability* **2019**, *11*, 4539. [CrossRef]
25. Hotelling, H. Stability in competition. *Econ. J.* **1929**, *39*, 41–57. [CrossRef]
26. D'Aspremont, C.; Gabszewicz, J.J.; Thisse, J.-F. On hotelling's "Stability in Competition". *Econometrica* **1979**, *47*, 1145–1150. [CrossRef]
27. Malleson, N. Building temporal dynamism into applied GIS research. *Appl. Spat. Anal. Policy* **2019**, *12*, 1–3. [CrossRef]
28. Kim, H.M.; Kwan, M.P. Space-time accessibility measures: A geocomputational algorithm with a focus on the feasible opportunity set and possible activity duration. *J. Geogr. Syst.* **2003**, *5*, 71–91. [CrossRef]
29. Newing, A.; Clarke, G.P.; Clarke, M. Developing and applying a disaggregated retail location model with extended retail demand estimations. *Geogr. Anal.* **2015**, *47*, 219–239. [CrossRef]
30. Geuens, M.; Brengman, M.; S'Jegers, R. Food retailing, now and in the future. a consumer perspective. *J. Retail. Consum. Serv.* **2003**, *10*, 241–251. [CrossRef]
31. Castillo-Manzano, J.I.; López-Valpuesta, L. Urban retail fabric and the metro: A complex relationship. Lessons from middle-sized Spanish cities. *Cities* **2009**, *26*, 141–147. [CrossRef]
32. Cervero, R.; Kang, C.D. Bus rapid transit impacts on land uses and land values in Seoul, Korea. *Transp. Policy* **2011**, *18*, 102–116. [CrossRef]
33. Tsou, K.; Cheng, H. The effect of multiple urban network structures on retail patterns–A case study in Taipei, Taiwan. *Cities* **2013**, *32*, 13–23. [CrossRef]
34. Ganning, J.; Miller, M.M. Transit oriented development and retail: Is variation in success explained by a gap between theory and practice? *Transp. Res. Part D Transp. Environ.* **2020**, *85*, 102357. [CrossRef]
35. Gao, S.; Wang, Y.; Gao, Y.; Liu, Y. Understanding urban traffic-flow characteristics: A rethinking of between ness centrality. *Environ. Plan. B Plan. Des.* **2013**, *40*, 135–153. [CrossRef]
36. Ding, R.; Ujang, N.; Bin Hamid, H.; Manan, M.S.A.; Li, R.; Albadareen, S.S.M.; Nochian, A.; Wu, J. Application of complex networks theory in urban traffic network researches. *Netw. Spat. Econ.* **2019**, *19*, 1281–1317. [CrossRef]
37. Wang, L.-N.; Wang, K.; Shen, J.-L. Weighted complex networks in urban public transportation: Modeling and testing. *Phys. A Stat. Mech. Appl.* **2020**, *545*, 123498. [CrossRef]
38. Fransen, K.; Neutens, T.; Farber, S.; De Maeyer, P.; Deruyter, G.; Witlox, F. Identifying public transport gaps using time-dependent accessibility levels. *J. Transp. Geogr.* **2015**, *48*, 176–187. [CrossRef]

39. Boisjoly, G.; El-Geneidy, A. Daily fluctuations in transit and job availability: A comparative assessment of time-sensitive accessibility measures. *J. Transp. Geogr.* **2016**, *52*, 73–81. [CrossRef]
40. Gan, Z.; Feng, T.; Wu, Y.; Yang, M.; Timmermans, H. Station-based average travel distance and its relationship with urban form and land use: An analysis of smart card data in Nanjing City, China. *Transp. Policy* **2019**, *79*, 137–154. [CrossRef]
41. Lin, J.; Ban, Y. Complex network topology of transportation systems. *Transp. Rev.* **2013**, *33*, 658–685. [CrossRef]
42. Kuby, M.; Tierney, S.; Roberts, T.; Upchurch, C. *A Comparison of Geographic Information Systems, Complex Networks, and Other Models for Analyzing Transportation Network Topologies*; NASA/CR-2005-213522; Arizona State University: Tempe, AZ, USA, 2005.
43. Soh, H.; Lim, S.; Zhang, T.; Tse, C.-K. Weighted complex network analysis of travel routes on the Singapore public transportation system. *Phys. A Stat. Mech. Appl.* **2010**, *389*, 5852–5863. [CrossRef]
44. Huang, A.; Xiong, J.; Shen, J.; Guan, W. Evolution of weighted complex bus transit networks with flow. *Int. J. Modern Phys. C* **2015**, *27*, 1650064. [CrossRef]
45. Meng, Y.; Tian, X.; Li, Z.; Zhou, W.; Zhou, Z.; Zhong, M. Exploring node importance evolution of weighted complex networks in urban rail transit. *Phys. A Stat. Mech. Appl.* **2020**, *558*, 124925. [CrossRef]
46. Brandes, U. A faster algorithm for betweenness centrality. *J. Math. Sociol.* **2001**, *25*, 163–177. [CrossRef]
47. Freeman, L.C. Centrality in social networks: Conceptual clarification. *Soc. Netw.* **1978**, *1*, 215–239. [CrossRef]
48. Barrat, A.; Barthélemy, M.; Pastor-Satorras, R.; Vespignani, A. The architecture of complex weighted networks. *Proc. Natl. Acad. Sci. USA* **2004**, *101*, 3747–3752. [CrossRef] [PubMed]
49. Opsahl, T.; Agneessens, F.; Skvoretz, J. Node centrality in weighted networks: Generalizing degree and shortest paths. *Soc. Netw.* **2010**, *32*, 245–251. [CrossRef]
50. Sabidussi, G. The centrality index of a graph. *Psychometrika* **1966**, *31*, 581–603. [CrossRef]
51. Sun, X.; Wandelt, S.; Linke, F. Temporal evolution analysis of the European air transportation system: Air navigation route network and airport network. *Transportmetr. B Transp. Dyn.* **2015**, *3*, 153–168. [CrossRef]
52. Fotheringham, A.S.; Brunsdon, C.; Charlton, M. *Quantitative Geography: Perspectives on Spatial Data Analysis*; Sage Publications: London, UK, 2000.
53. Wang, F. *Quantitative Methods and Applications in GIS*; Taylor & Francis: Boca Raton, FL, USA, 2006.