

Article

Exploring Spatial Features of Population Activities and Functional Facilities in Rail Transit Station Realm Based on Real-Time Positioning Data: A Case of Xi'an Metro Line 2

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Abstract: The rail transit station realm is an important urban spatial node that carries various behavioral activities and multiple functions. In order to accurately identify the spatial and temporal distribution of population activities and functional facilities in the rail transit station realm and understand the dynamic influence relationship between them, this paper takes four different types of stations of Xi'an Metro Line 2 as the research object, using real-time positioning data to represent population activities and points of interest (POIs) to represent functional facilities. An analytical framework combining the spatial point pattern identification technique and ordinary least squares (OLS) regression model is proposed. The results show that (1) there is spatial and temporal heterogeneity in the population activities in the rail transit station realm; the density distribution of population activities in different time periods shows the characteristic of clustering within 500 m of the station, regardless of working days or off days; (2) the distribution of shopping service POI, catering service POI, and living service POI in different station realms shows the feature of clustering around the stations; (3) the catering POI, living POI, shopping POI and transportation POI have positive attraction to population activities in different time periods; the constructed OLS model can basically explain the influence relationship between various functional facilities and population activities in all time periods. The conclusions can help city managers understand the spatial and temporal distribution and intrinsic mechanisms of population activities and functional facilities from a microscopic perspective and provide an effective decision-making basis for optimizing the allocation of functional resources in the station realm.



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Keywords: rail transit station realm; spatiotemporal features; real-time positioning data; POI

1. Introduction

The rapidly developing urban subway system has greatly improved the accessibility of the area around the station and attracted a large number of people and various services to gather in this area, thus forming an urban space with the station as the center and people's daily activities influenced by the station to a certain extent [1,2]. This is the rail transit station influence realm (referred to as station realm in this paper). In Hong Kong, rail transit shares 43.9% of the daily public transportation trips of permanent residents, and nearly 50% of citizens live within a radius of 500 m from the station [3]. In Tokyo, where rail transit is developed, the rail transit travel share rate in Tokyo's 23 districts exceeded 77% in 2018 [4]. In Northwest China, where the development of rail transit is relatively late, the share of rail transit in urban public transport in Xi'an will be over 50% in 2021 [5]. In addition, rail transit-oriented development models such as TOD [6], station-city integration [7], and station integrated development [8] are favored by urban planners and managers around the world, especially for developing countries facing traffic congestion problems caused by rapid urbanization. Thus, the urban rail station area has become an important region to

play the function of gathering the city, to create public transportation to support and guide urban development, and to improve the quality of the urban environment [9,10]. Therefore, in order to develop a policy for sustainable spatial development of the station realm that meets public demands, urban managers and designers must improve their knowledge of the spatial pattern of the area. This is especially true when understanding the intrinsic influence relationships between functional facilities and population activities.

In general, the construction of major transportation infrastructure affects the distribution of urban elements and thus reshapes the spatial pattern of cities [11,12]. In previous studies, many scholars have revealed the spatial features of the rail transit station domain in terms of land use structure [13,14], industrial distribution [15,16], etc., but there is little literature addressing the detailed revelation of the spatial features of human activities in the station domain, especially considering the dynamic distribution changes of population activities in space under different time periods. Meanwhile, most studies have focused on the mechanisms of rail transit's influence on land use [17,18], accessibility [19,20], and land price [21,22] around stations, while few studies have explored the relationship between urban functions and population activities, especially considering the dynamic influence mechanisms under different time periods of working days and off days. The public space around the rail station is a special space dominated by the activity trajectory of residents, and people are the main actors of activities in the public space [23]. Therefore, population activities are an important part of the space of the rail transit station realm. Consequently, to complement the above research status gap, we attempt to identify the spatial point pattern of population activities and urban functions in the station realm using more refined and real-time positioning big data on the ArcGIS platform and further develop regression models to explore the dynamic influence mechanism between population activities and urban functions.

In today's rapidly developing information technology, big data has greatly enriched the methods and ways for researchers to obtain data. Compared with the traditional survey methods based on observation and experience, big data has the advantages of rich sources, large sample size, and real-time, which can reflect the characteristics of survey subjects more objectively [24]. Although many researchers have used multi-source data such as mobile phone signaling [25,26], the Metro Automatic Fare Collection System (Metro AFC) [27,28], social media [29–31], and Wi-Fi signaling technology [32] to explore user travel activities and distribution features, the above big data sources have some limitations in the use of the microscopic station space region. Mobile phone signaling technology is usually used to extract the Original and Destination (OD) data of residents' traffic travel [33], but the distribution density of communication base stations is small (the coverage radius of urban areas is generally 100~500 m) [34]. Using the base station to send and receive data may cause spatial positioning errors, which in turn affects the accuracy of crowd identification. Metro AFC is a system that uses automatic ticket gates to record the exit and entry station and time of each passenger and uploads this data to a database with a specific frequency [35], the data can provide a large amount of passenger travel information, including passenger codes, entrance times, exit times, departure and destination stations, etc. However, the AFC data are only applicable to the statistics of the total passenger flow of the rail transit network, and the real-time passenger distribution in space is not available [36]. In addition, the use of social media platforms such as Facebook, Twitter, and Weibo to collect analytical data related to population activity trajectories is not sufficient to represent the activity characteristics of people of all ages, since most of the contributors are young people [37]. The Wi-Fi signaling technology needs to plan and deploy significant signal equipment to ensure full coverage of signals in the station area region in order to ensure the accuracy of data collection; however, this greatly increases the research cost [38]. In this study, we choose the mobile terminal program developed by WeChat, Easygo applet (which displays the thermal distribution of people flow in the currently selected area based on the map). These data have the following advantages [39,40]: (1) strong real-time performance. The data of WeChat comes from the GPS positioning information of the mobile intelligent

terminals of the crowd. It has the characteristics of dynamic update and real-time feedback; (2) high accuracy: the extraction range of the data of Easygo is only a $25\text{ m} \times 25\text{ m}$ grid, which is more suitable for research at the micro-scale; (3) high coverage: the positioning data of Easygo mainly comes from WeChat, a social software owned by Tencent, which covers a wider population in China and has strong utilization value; (4) easy availability: Easygo directly provides an API interface to make data easier to obtain directly. Therefore, the real-time positioning data of Easygo is suitable for this paper to identify the population distribution and changes in the station realm at the microscopic scale.

The study has two main objectives. The first one is to demonstrate the use of positioning big data to explore the distribution features of population activities and functional facilities within the study area at the microscopic scale. The second objective is to analyze the relationship between population activities and functional facilities over time using ordinary least squares (OLS) models. In summary, the main purpose of our study is to take the rail transit station realm as the research unit, use real-time positioning data from Easygo and POI data from AutoNavi Map, and visualize and analyze the spatial distribution of population activities and functional facilities within the station realm based on the spatial pattern tool of geographic information system (GIS). Then, an ordinary least squares (OLS) model is used to further explore the correlation between the spatial characteristics of population activity distribution and functional facilities and to analyze the dynamic influence relationship between them.

The main contributions of this paper are as follows:

1. Expansion of theoretical research. Focusing on the dynamic spatial distribution changes of population activities, we study in depth the inner mechanism of population activities and various functional facilities, which enriches the theoretical system of spatial pattern research in the station realm.
2. Innovation in research scale. By taking the station realm as an independent and complete spatial unit, we break the limitation of traditional urban spatial boundaries, and thus realize the spatial pattern features of population activities and functional facilities from a more microscopic perspective.
3. Innovation of technical means. We use real-time and more accurate positioning data (Easygo data), an analysis framework combining spatial point pattern identification technology, and an ordinary least squares (OLS) regression model. Based on identifying the spatial distribution features of population activities and functional facilities in the station realm, the dynamic influence relationship between the two is further reflected.

The rest of this paper is organized as follows. Section 2 presents the study area. Section 3 explains the basis for selecting research stations, the method for defining the station realm, the source of the study data, and the analysis method. Section 4 shows the results of the kernel density analysis and OLS regression analysis. Sections 5 and 6 provide a discussion and summary of the analysis results.

2. Study Area

Xi'an is the capital city of Shaanxi Province and the political, economic, and cultural center of Northwest China, with a population of 12.95 million [41]. At present, there are eight rail transit lines in operation in Xi'an. In 2011, the first Metro Line 2 was put into operation, with a total length of 26.7 km and a total of 21 stations [42]. It is not only the line with the highest average daily passenger flow in Xi'an (Figure 1), but also the core line that overlaps with the city's central axis and connects multiple functional development areas in the north and south. Metro Line 2 is a very important case study, because it has a profound impact on the urban spatial structure along and around the station. Therefore, fully grasping its characteristics and laws has strong reference significance for the sustainable development of the future metro station surrounding areas in Shaanxi Province and even the entire Northwest China.

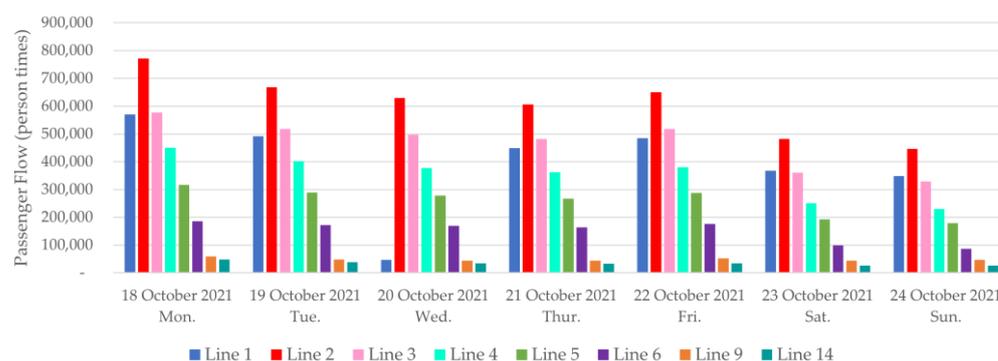


Figure 1. One week passenger flow statistics chart of Xi'an Metro. Source: Xi'an Metro Official Weibo Account, <https://weibo.com/xianditie> (accessed on 18 to 24 October 2021).

In this paper, each station of Line 2 is classified based on the method proposed by Duan Degang et al. [43] to classify station types by the land use composition around the station (Table 1). Under the premise of including all types and considering the geographical location in Xi'an where the stations are located (Figure 2), we selected a total of four typical stations, namely Xing Zheng Zhong Xin Station, Long Shou Yuan Station, Bei Da Jie Station, and Wei Yi Jie Station, as the research objects of this paper (Table 2).

Table 1. Classification basis of rail transit stations.

Station Types	Classification Basis
Residential	The planning and construction of land around the station is mainly residential land; the proportion of land is $\geq 45\%$.
Public Service	The planned land around the station is mainly for administrative offices, cultural education, and other public administration and public services, with the proportion of land greater than 15%, and the proportion of residential land is $< 45\%$.
Commercial Service	The planned land around the station is mainly commercial, business, entertainment, and recreation land, with the proportion of land $> 15\%$, and the proportion of residential land is $< 45\%$.
Transportation	The station is intended to connect with external transportation facilities. The proportion of land for transportation facilities is $> 30\%$, and the proportion of residential land is $< 45\%$.
Industrial	The planning land around the station is mainly industrial land and storage land, with a proportion of land $> 10\%$, and the proportion of residential land is $< 45\%$.
Hybrid	The planning land around the station is diverse, with no obvious advantageous land, and the ratio is more balanced.

Table 2. Classification results of four station types.

Code	Name	Abbreviation	Location	Land Use Nature
a	Xing Zheng Zhong Xin STN	XZZX	Second Ring Road–Third Ring Road	Hybrid
b	Lou Shou Yuan STN	LSY	First Ring Road–Second Ring Road	Residential
c	Bei Da Jie STN	BDJ	First Ring Road	Commercial service
d	Wei Yi Jie STN	WYJ	Second Ring Road–Third Ring Road	Public service

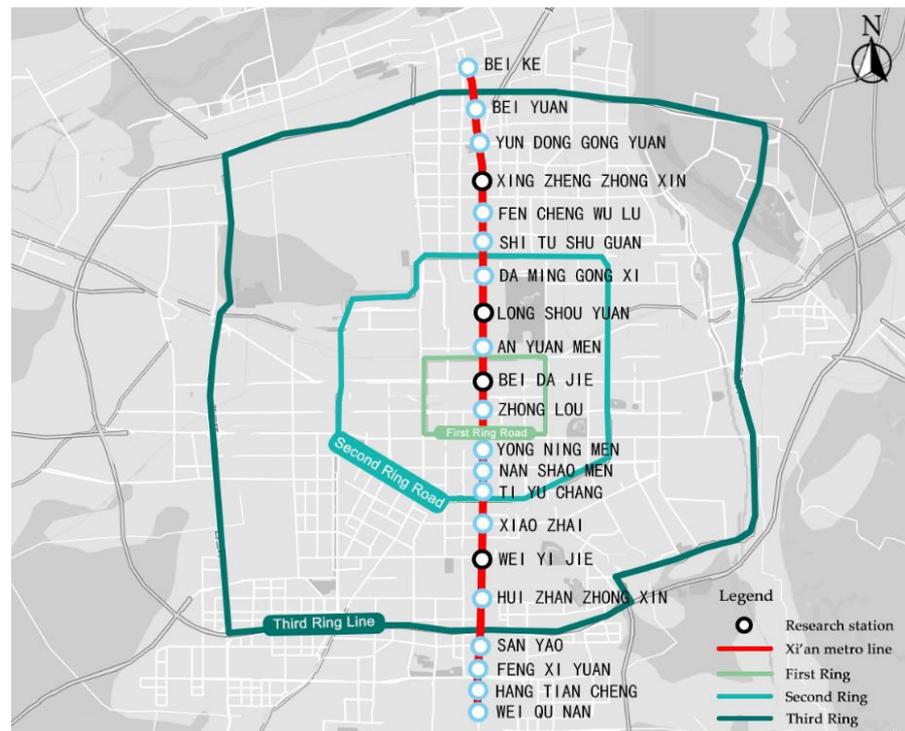


Figure 2. The location of four research stations on Xi’an Metro Line 2.

3. Materials and Methods

As shown in Figure 3, a five-stage research methodology was used: (i) determination of station realm; (ii) data collection and processing; (iii) spatial point pattern identification; (iv) regression analysis; (v) feature induction. stage (i) defines the scope of the station realm, stage (ii) is the preparation of the data for analysis, and stages (iii) through (v) include the analysis of data and the summary of results. Specifically, the stage of spatial point pattern identification reveals the characteristics of population activities and urban function distribution in the station realm, and the spatial relationship analysis is the further explanation of the characteristics and phenomena.

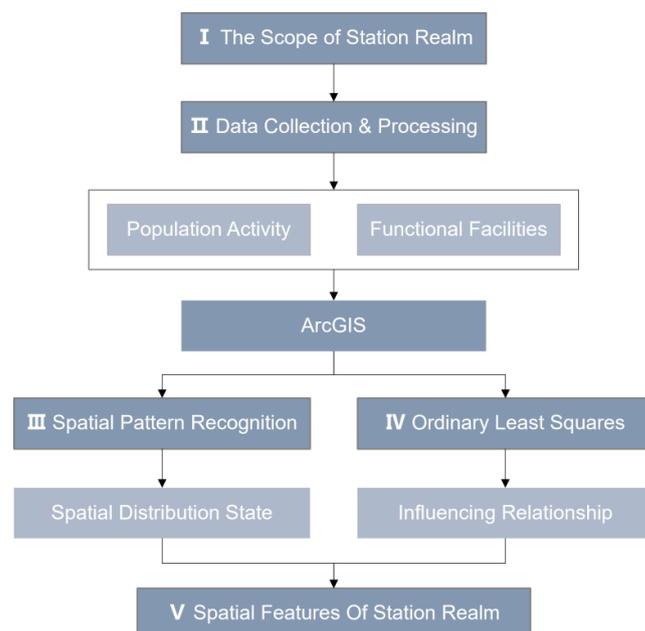


Figure 3. The framework of the research process.

3.1. Rail Transit Station Realm

The walking scale is usually the core element to define the scope of the rail transit station realm [44]. At present, the definition of the rail transit station area is mainly based on the area in which the station entrance can be reached within 10 to 15 min walking distance and that is closely related to the rail function [9,45]. However, in practice, since the scale standard is not a fixed value, the station area range value tends to vary from city to city. For example, the walking distance of the station realm in Canadian cities is mostly between 300 m and 900 m, while it is 400 to 800 m in the US [46,47]. Hyungun Sung delineated the Seoul rail transit station impact area with a reasonable walking range of 500 m [20]. In Shenzhen, China, some scholars proposed that the public habitual walking time is mostly concentrated in a 6~10 min interval walking range, or about 400~700 m, based on the survey [48]. In addition, some scholars believe that the rail transit station realm is not simply delineated by abstract geometric radius; it is also influenced by topographic space, road pattern, plot function, and other factors [49].

Therefore, taking the BDJ Station of the Xi'an Metro Line 2 as an example, we firstly use questionnaires and infrared velocimetry to conduct field surveys on the acceptable walking time (Figure 4a) and average walking speed (Figure 4b) of pedestrians around the BDJ Station, respectively. Secondly, the walking time of 10 min and average walking speed of 1.18 m/s are selected based on the relevant literature and actual demand, and the walking scale is calculated as 708 m. The walking scale is used as a radius to set up a buffer zone on ArcGIS and is adjusted according to the actual situation of urban roads and land integrity to finally obtain the station realm of BDJ (Figure 5). Other research station realm ranges in this paper are defined by the same method (Figure 6).

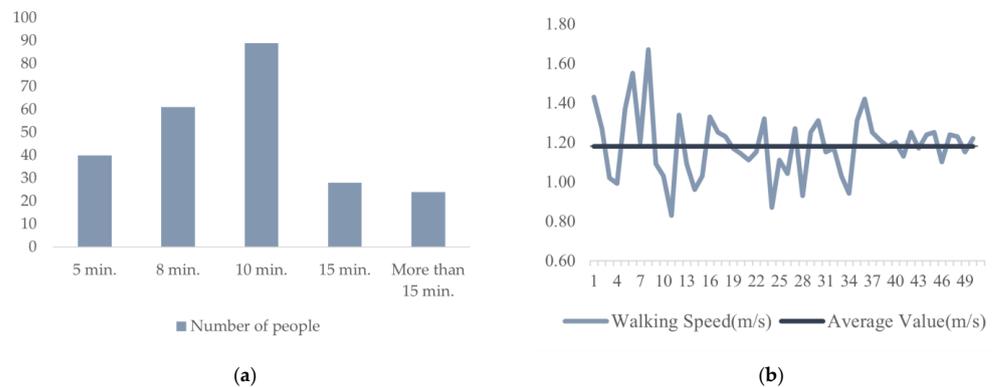


Figure 4. Pedestrian walking time (a) and walking speed (b) in BDJ station realm.

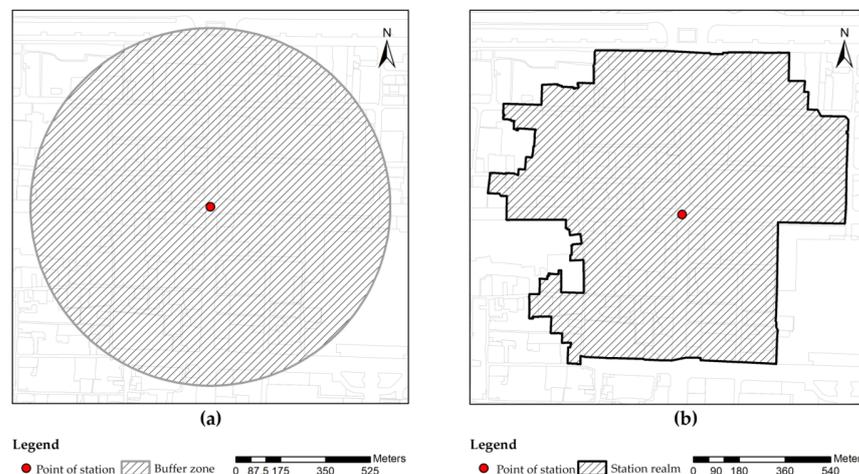


Figure 5. The scope adjustment process of the BDJ station realm: (a) before adjustment; (b) after adjustment.

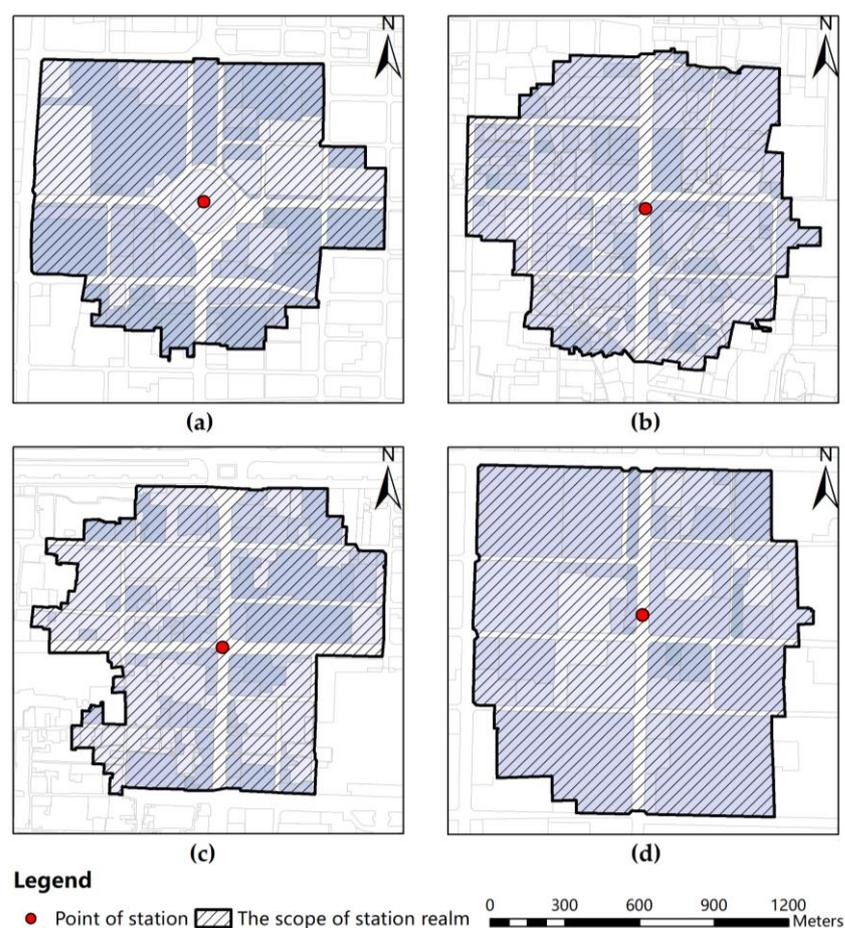


Figure 6. Scope of the four research station realms: (a) XZZX Station, (b) LSY Station, (c) BDJ Station, (d) WYJ Station.

3.2. Data Source and Collection

3.2.1. Data Source

As mentioned above, this study considers the spatial distribution of pedestrians and urban functions simultaneously. The data mainly comes from WeChat's Easygo applet and AutoNavi Map's API. In addition, data such as pedestrian walking time and walking speed were collected through field surveys.

WeChat is an instant messaging software launched by China's Tencent on 21 January 2011. It supports mobile operating systems such as Android and IOS. As of 30 June 2021, the software's monthly active users (MUA) exceeded 1.2 billion, making it the most active social software in China [50]. In addition, WeChat accounts for about 69.2% of China's communication software [51]; excluding children, elementary school students, and the elderly, who rarely use mobile phones, the data can fully cover various activities of the population of all ages. Easygo is a WeChat built-in applet. By recording the real-time location information of WeChat users, it gives the real-time pedestrian location in the form of spatial point data, which has the characteristics of low acquisition cost, high spatial resolution, and real-time dynamic change. Therefore, the above points are the reasons why the data of Easygo can reflect the spatial distribution features of pedestrians in this study.

POI (Point of interest) data mainly include spatial information and attribute information data of geographic entities closely related to people's lives. It can quickly and intuitively obtain the distribution of various functions in urban space, which is superior to traditional research data [52]. In addition, different from the previous studies on the relationship between rail stations and surrounding urban land through the nature of land

use, POI data is more microscopic and has more advantages in data accuracy, which can more intuitively reflect the spatial agglomeration characteristics of urban functions [53]. In this study, POI mainly reflects the spatial distribution of urban functions in the station realm and conducts correlation analysis with the spatial activity characteristics of pedestrians.

In summary, for the scope of this study, Easygo's point data represent population activities; AutoNavi Map's points of interest represent urban functional facilities.

3.2.2. Data Collection

The data for population activities and POIs in this paper are sourced from the Tencent Location Big Data Service window (<https://heat.qq.com/index.php>, accessed on 15 November 2021) and the AutoNavi Map's Public Application Programming Interface (API) (<https://lbs.amap.com>, accessed on 30 December 2021). These applications can collect all the data in the delimited area and export them to csv files. In order to protect the privacy of WeChat users, we only extract the geographic location and time information of users when collecting data on Easygo and do not collect data containing personally identifiable information such as name, age, and gender. Similarly, we only extract the type of service facilities and geographic location in extracting the points of interest of AutoNavi map. The details are shown in Table 3.

Table 3. The specific metadata of the obtained original dataset.

Data Attributes	Easygo	AutoNavi Map
Location	Longitude	Longitude
	Latitude	Latitude
Time information	Date	–
	Time period	
Ancillary information	Number of active people	Place name
Data categorization		Place address
Data ID	Date	City functional nature

Existing studies have shown that the daily activities of the inner-city population usually vary cyclically on a weekly basis and that there are some differences in the distribution of the population between working days and off days [39,54]. In this study, the Easygo data were collected for 7 consecutive days from 15 November to 21 November 2021 (20 and 21 were off days and 15 to 19 were working days) using the boundary of each research station realm as the data collection scope (Figure 7); the collection time was from 7:00 a.m. to 22:00 p.m. (according to the Xi'an metro operation time), and a total of 193,592 raw data in CSV format, including activity date, activity number, longitude and latitude, were collected. In order to accurately identify the spatial distribution features, after preliminary experimental validation, we selected the 17th (Wednesday) and 20th (Saturday) to represent the population activities on working days and off days.

The POI data were also collected within the boundaries of each research station realm; the collection time was 30 December 2021, with a total of 12,283 pieces of data collected. In this paper, the classification of the collected POI data refers to the relevant literature [53,55]; 10 categories closely related to daily life are selected according to the primary classification code as shown in Appendix A. The quantity statistics of POI data are shown in Figure 8. To make the research results more convincing, we remove the POIs of public service facilities, because the amount of data is too small in each study station realm, and public facilities such as restrooms, telephone booths, and newsstands would not be overly attractive to pedestrians under normal circumstances.

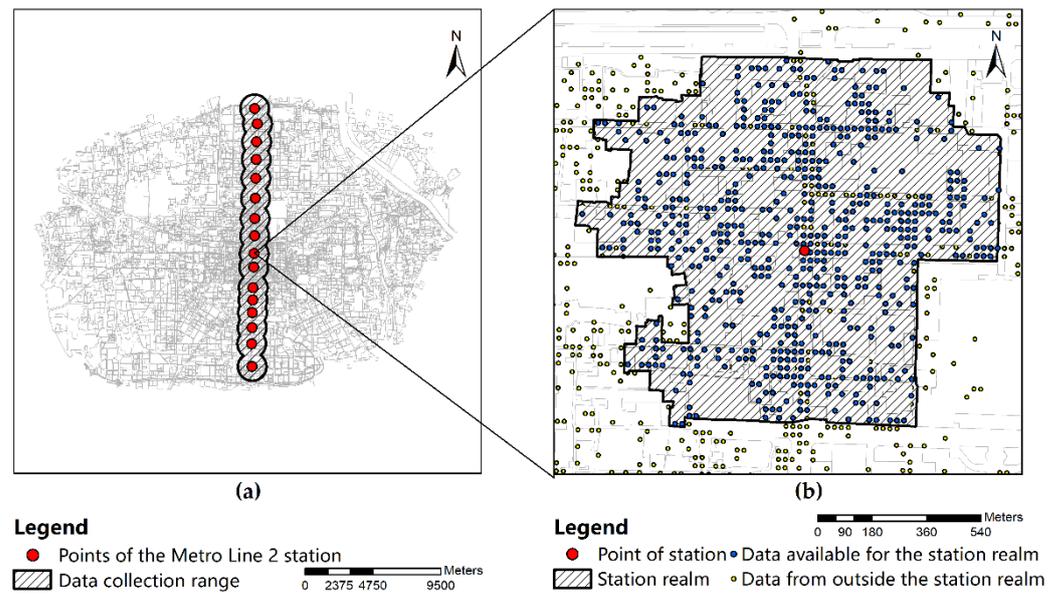


Figure 7. Data collection area and partial data. (a) Data collection area of Metro Line 2; (b) Point data distribution of population activities.

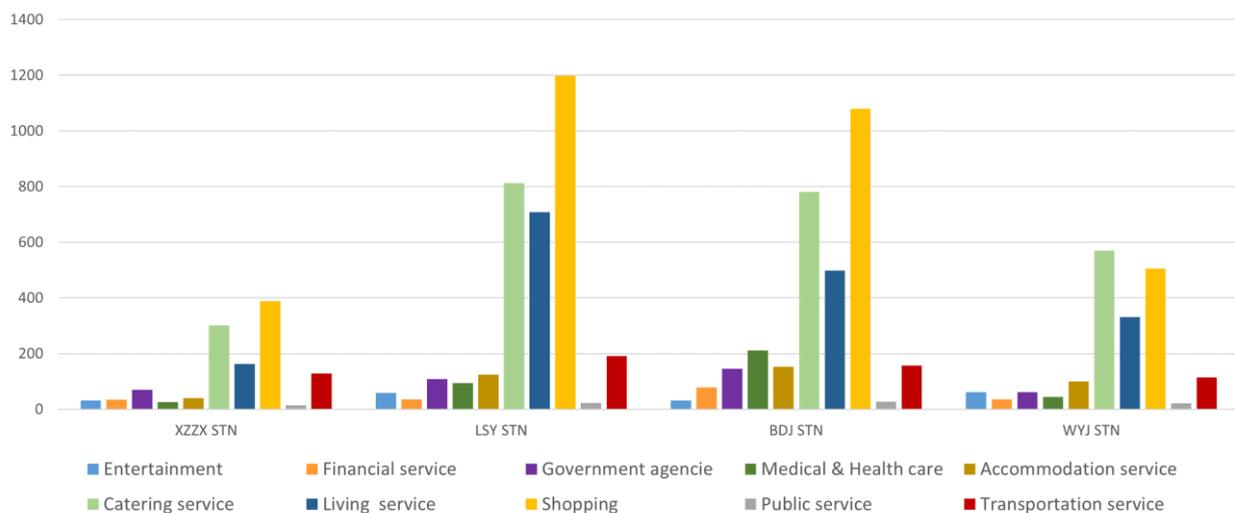


Figure 8. Statistics on the number of POIs for each research station realm.

All the above data were converted from raw data to point data based on latitude and longitude information using the ArcGIS platform and were summarized and integrated according to the names of the stations in order to prepare for the next stage.

3.3. Data Analytical Methods

In order to visualize the location, shape and size of the spatial clustering of the study objects, we used kernel density to identify the spatial point pattern of human activities and urban functions, and explored the basic features and patterns of spatial distribution of each research station realm. In addition, we further analyzed the changing relationship between population activities and urban functions in the station realm space by ordinary least squares (OLS).

3.3.1. Kernel Density Analysis

Kernel Density Analysis can reflect the distribution of the whole area by showing the aggregation of points by density based on the values of the input point elements and their

distribution and produce a continuous raster graph (heat map) [56]. In this study, kernel density analysis is used to explore the state of spatial distribution of human activities and functional facilities in each station realm. Kernel density analysis has been widely used in the field of urban space-related research [57–59]. The calculation equation is as follows:

$$Density = \frac{1}{(radius)^2} \sum_{i=1}^n \left[\frac{3}{\pi} \cdot pop_i \left(1 - \left(\frac{dist_i}{radius} \right)^2 \right)^2 \right] \text{ For } dist_i < radius \quad (1)$$

where $i = 1, \dots, n$ are the input points. Only points in the sum are included if they lie within the radius distance of the (x,y) position. $Dist_i$ is the distance between point i and the (x,y) position.

3.3.2. Ordinary Least Squares

Ordinary least squares (OLS) is the most commonly used regression method to assess the relationships between urban spatial elements [60,61]. In this paper we focus on the coefficient of each explanatory variable, which reflects the strength and type of relationship between the explanatory and dependent variables. When the sign associated with the coefficient is positive, the coefficient is positively related to the dependent variable, and conversely, it is negatively related. In addition, probabilities (p -values) can help us find which variables are statistically significant ($p < 0.01$) and thus deserve further analysis. The model of OLS can be described as Equation (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon \quad (2)$$

where y is the dependent variable, x_n is the explanatory variable, β_n is the regression coefficient, and ε is the random error. In this study, the number of active people in the study station realm is the dependent variable, and the number of POIs in each functional facility is the explanatory variable. Table 4 shows the explanatory variables and their descriptive statistics.

Table 4. Definition and descriptive statistics of explanatory variables.

Code	Explanatory Variables	Total	Mean	Standard Deviation
V1	Entertainment POIs	181	45.25	16.50
V2	Financial Service POIs	184	46.00	21.35
V3	Government Agency POIs	386	96.50	39.03
V4	Medical and Health Care POIs	376	94.00	83.29
V5	Accommodation Service POIs	418	104.50	48.14
V6	Catering Service POIs	2466	616.50	235.76
V7	Living POIs	1702	425.50	233.29
V8	Shopping POIs	3173	793.25	404.96
V9	Transportation Service POIs	592	21.50	5.45
V10	Public Service POIs	86	148.00	34.32

4. Results

4.1. The Spatial Distribution of Population Activities

The size of the search radius in the kernel density analysis has a significant effect on the refinement of the analysis results. According to the related literature [62], we took the average side length of 200 m of the natural blocks composed of roads in each study station realm as the threshold value and took the radius of 50 m, 100 m, 150 m, 200 m and above, respectively, for the detection analysis. The results show that there are too many first-level hotspots within 100 m (Figure 9a) and too many integrated above 200 m (Figure 9e), while the hotspot levels between 100 and 200 m are basically stable (Figure 9b–d), which only affects the smaller levels of hotspots. Therefore, this paper takes the middle number of 150 m as the search radius.

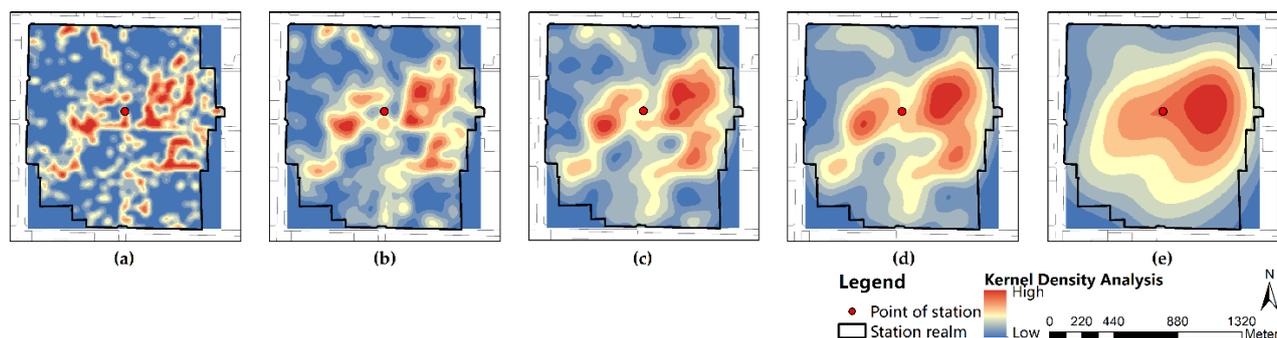
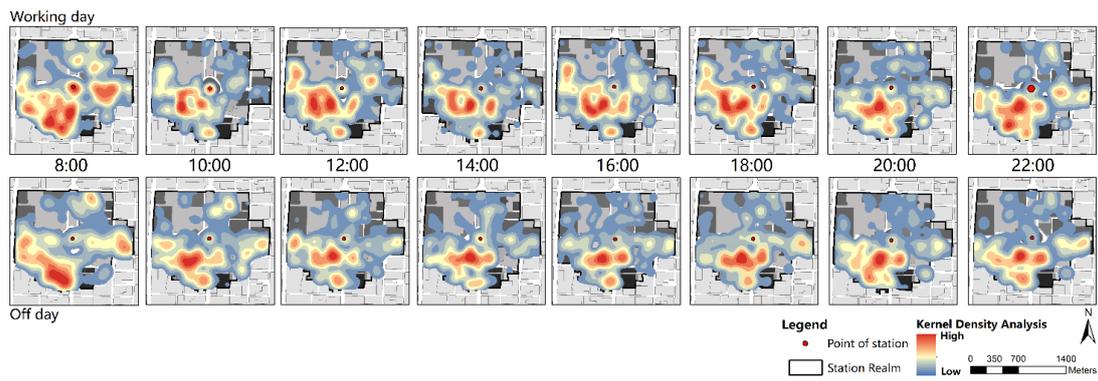


Figure 9. Visualization of kernel density analysis results under different scale search radius: (a) 50 m radius, (b) 100 m radius, (c) 150 m radius, (d) 200 m radius, (e) more than 200 m radius.

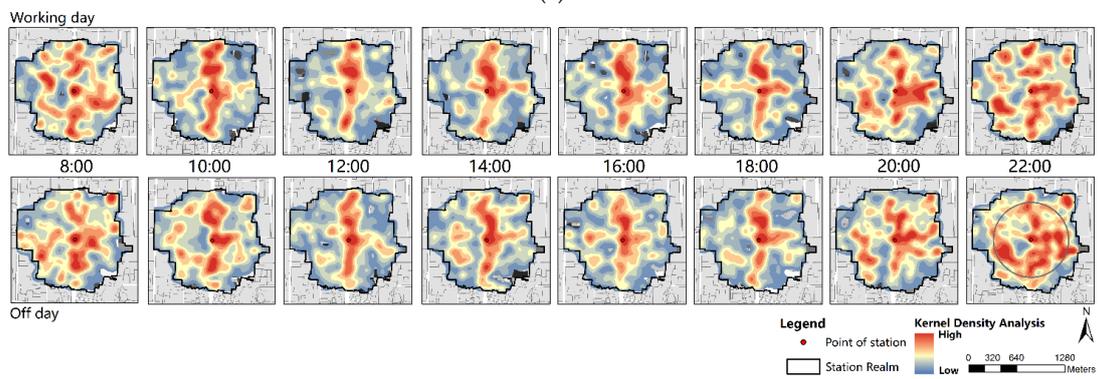
The visualization of the kernel density results of the population activities in each research station realm is shown in Figure 10. The results show that the location, shape, and size of the population activity aggregation area during the day change spatially along with time, which indicates that the population activity in the station realm is spatially non-stationary. In terms of the overall spatial distribution, we measured the distance between the peak areas of the nuclear density of population activity (dark areas) and the stations in each research station realm using the metric tool of ArcGIS, and we found that these peak areas were mainly distributed within 500 m of the station perimeter (Figure 11), which indicates a high level of population activity within this range. In terms of spatial position, the population activities in the XZZX station realm are mainly concentrated in the large shopping mall on the south side; the population activities in the LSY station realm are mainly distributed in the neighborhoods and commercial complexes around the station; the population activities in the BDJ station realm are mainly concentrated in a number of large medical institutions on the east side of the station and the large shopping mall on the south side; there are several universities and urban villages in the WYJ station realm, so the population activities are mainly concentrated in these areas.

In terms of temporal distribution features, the peak kernel density of population activities in the four study station realms for each period on working days and off days is shown in Figure 12. During working days, population activity is basically dominated by commuting characteristics, with the morning peak period generally lasting from 7:00 a.m. to 9:00 a.m., and the evening peak mainly concentrated between 6:00 p.m. and 8:00 p.m. On off days, the peak time for population activity is generally at or after 11:00 a.m. This indicates that on off days people choose to be out later compared to working days due to the absence of demands such as work and school. In addition, the mean value of the kernel density of population activity is higher on off days than on working days after 11:00 a.m., which could indicate that the population is more active on off days than on working days during that period.

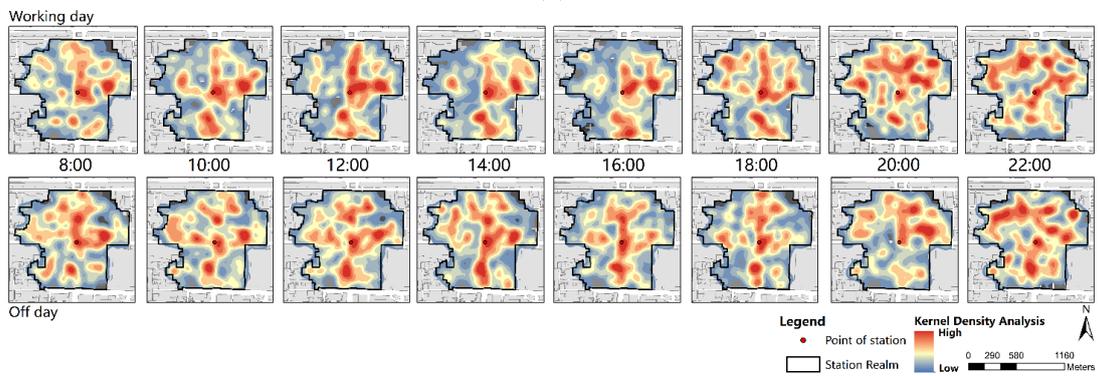
It is worth mentioning that the population activity in the LSY Station realm shows a continuous increase between 6:00 and 10:00 p.m., and the kernel density of population activity reaches its highest value at 10:00 p.m. The field survey reveals that a large number of night markets appear around the station during this period, which attracts the population to gather here.



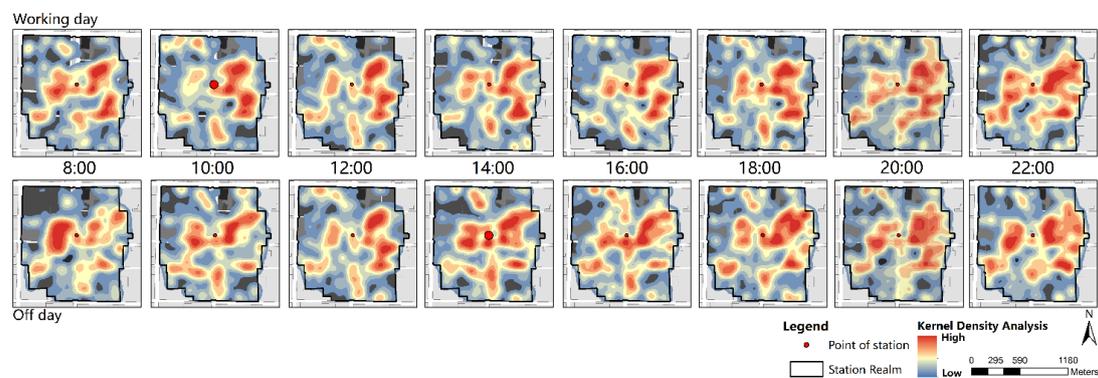
(a)



(b)



(c)



(d)

Figure 10. Temporal and spatial distribution of human activities in each study station realm: (a) XZZX Station, (b) LSY Station, (c) BDJ Station, (d) WYJ Station.

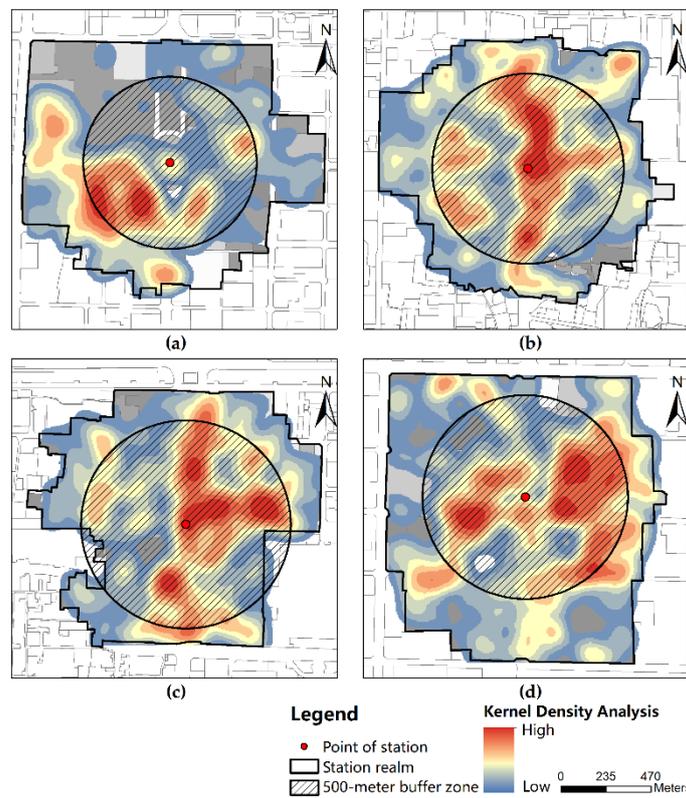


Figure 11. Peak nuclear density of population activity within 500 m of each research station realm: (a) XZZX station realm; (b) LSY station realm; (c) BDJ station realm; (d) WYJ station realm.

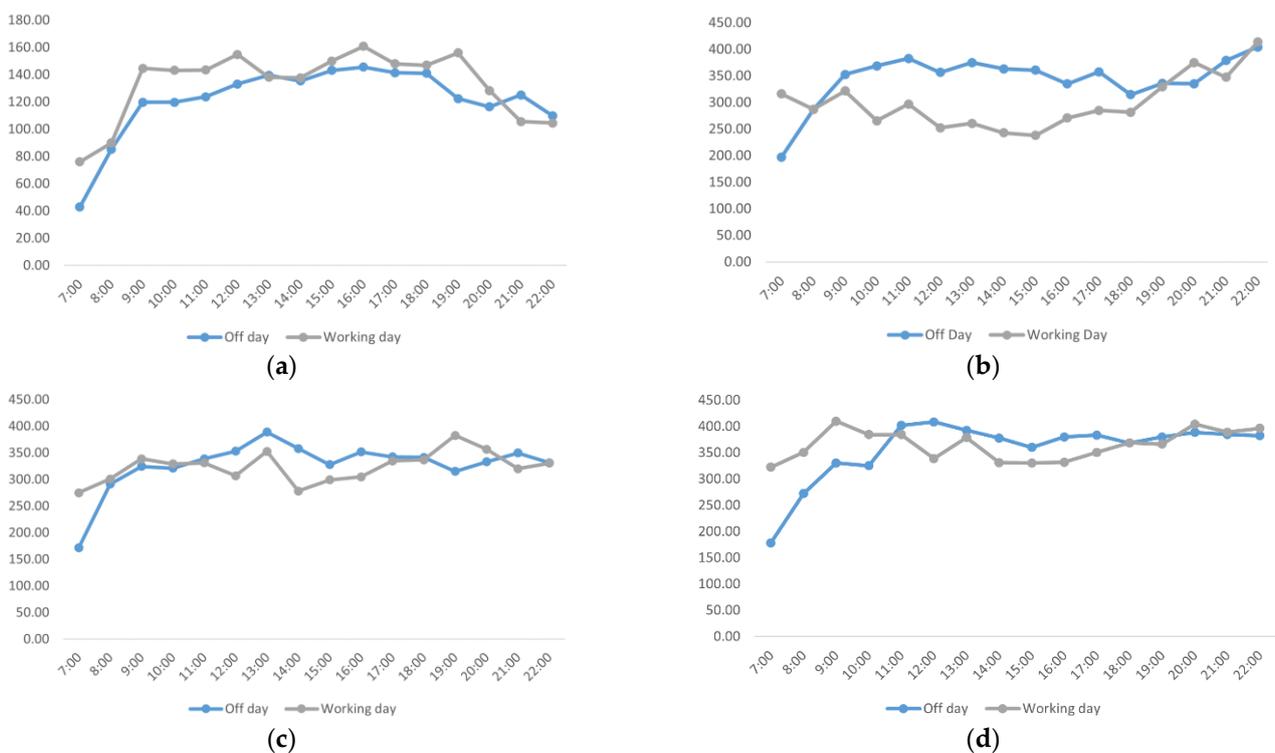


Figure 12. The peak kernel density of population activities in the study station realm during working days and off days: (a) XZZX Station, (b) LSY Station, (c) BDJ Station, (d) WYJ Station.

4.2. The Spatial Distribution of Functional Facilities

The results of the kernel density analysis for each type of POI in the four research station realms are shown in Figure 13.

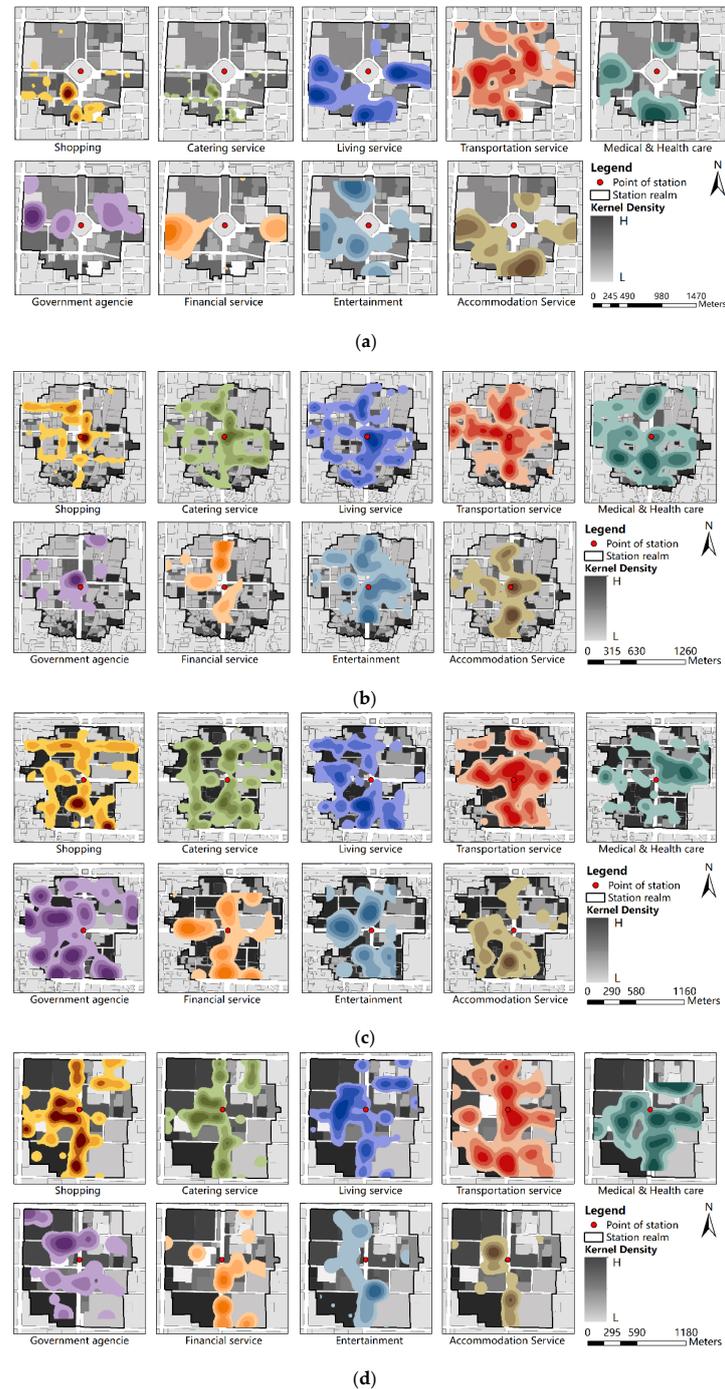


Figure 13. Kernel density analysis of each functional POI in study station realm. The analysis results of the (a) XXZX Station; (b) LSY Station; (c) BDJ Station; (d) WYJ Station.

As shown in Figure 13a, the POIs of various functions in the Xing Zheng Zhong Xin station realm show a spatial distribution feature of high in the south and low in the north. The POIs of various functional facilities in the Long Shou Yuan station realm are generally distributed around the station (Figure 13b), especially the six types of facilities, namely shopping POIs, catering POIs, living POIs, transportation POIs, government agency POIs, and accommodation POIs, which have the characteristic of higher density the closer they

are to the station. As shown in Figure 13c, the distribution features of each functional facility in the Bei Da Jie station realm differ significantly. Five types of facilities, namely shopping POI, catering POI, living POI, accommodation POI, and financial POI, are more densely distributed in the south of the station realm than in the north. In addition, the density distribution of medical and health POIs is much higher in the east-central part of the station realm than in other regions. The results of the kernel density analysis of the station realm of Wei Yi Jie (Figure 13d) show that we find that the POIs of each functional facility are distributed along both sides of Chang'an South Road (north–south direction) and Chang Ming Road (east–west direction).

In general, shopping service POIs, catering service POIs, and living service POIs show spatial distribution features around the stations in each research station realm. However, the different land composition within diverse types of station realms makes the density distribution features of functional facilities vary significantly, such as entertainment POIs, government agency POIs, and medical and health POIs. However, through comparative analysis, we found that population activities and functional facilities have geographically similar peak kernel density coverage areas in the station realm, which indicates that areas with a high-density distribution of functional facilities within the station realm are more attractive for people to move around in.

4.3. Spatiotemporally Varying Impact of Functional Facilities on Population Activities

In order to more accurately assess the dynamic influence relationship between functional facilities and population activities, based on the boundaries of each study station realm, a grid with an image element scale of 25×25 m was created on the ArcGIS platform as the spatial statistical unit for the regression analysis in this paper (which is consistent with the collection scale of our population activity data). Then, the dependent variable (population activity) and the explanatory variable (functional facility) were connected to this grid for OLS regression analysis. However, variance inflation factors (VIFs) also needed to be calculated to avoid multicollinearity among the explanatory variables of the model and to exclude variables with VIF values greater than 10 [63]. As shown in Table 5, the VIF values of each explanatory variable in the four research station realms are less than 10, indicating that there is no cointegration among the explanatory variables and that they are suitable to form a regression model.

Table 5. VIF values of each explanatory variable in the research station realm.

Node	Explanatory Variables								
	V1	V2	V3	V4	V5	V6	V7	V8	V9
a	1.077146	1.052008	1.003226	1.153893	1.167818	1.281808	1.331359	1.177643	1.003262
b	1.136314	1.036239	1.002621	1.089429	1.189986	1.414797	1.365890	1.355947	1.015039
c	1.121328	1.174433	1.101934	1.048102	1.073300	1.185059	1.509962	1.322163	1.036715
d	1.038070	1.014958	1.006687	1.033388	1.085360	1.369630	1.172820	1.377559	1.007235

As shown in Table 6, the explanatory variables in the Xing Zheng Zhong Xin station realm (hybrid type)—medical and health POIs (V4), catering POIs (V6), living POIs (V7), shopping POIs (V8), and transportation POIs (V9)—have a positive relationship with population activity during almost all hours of the working days and off days. This indicates that the higher number of these functional facilities is also more attractive for population activities. In particular, the catering POIs and living POIs have a significant positive correlation. The entertainment POI (V1) has a negative relationship with population activity most of the time, indicating that an increase in the number of such functional facilities does not attract more activity. In addition, the financial service POI (V2) and government agency POI (V3) have a positive relationship with population activities on working days, while the off days have more of a negative relationship.

Table 6. The OLS regression results for the XZZX station realm.

Day	Period	Explanatory Variables									
		Intercept	V1	V2	V3	V4	V5	V6	V7	V8	V9
Working Day	8:00	0.0658	−0.1072	0.1199 *	−0.0048	−0.0790	0.0930 *	0.0091	0.0064	0.0668 *	0.0114
	10:00	0.1023	−0.0012	0.1214 *	0.0083	0.0165	0.0070	0.0135	0.0086	0.0495 *	0.0614 *
	12:00	0.1084	−0.0349	0.0480	0.0025	0.0934	−0.0313	0.0342 *	0.0282 *	0.0571 *	0.0954 *
	14:00	0.0911	−0.0738	−0.0022	0.0364 *	0.0432	0.0347	0.027 *	0.0272 *	0.0260	0.0607 *
	16:00	0.1093	0.0150	0.0765	0.0452 *	0.0352	0.0352 *	0.0453 *	0.0164 *	0.0334	0.0823 *
	18:00	0.1037	−0.0458	0.0612	0.0113	0.1589 *	0.0154	0.0370 *	0.0191 *	0.0306	0.0269
	20:00	0.0887	−0.0889	0.0181	−0.0140	0.1215 *	0.0287	0.0485 *	0.0202 *	0.0193	0.0554 *
	22:00	0.0742	−0.0083	−0.0271	−0.0163	−0.0485	0.0786	0.0328 *	0.0157 *	0.0618 *	0.0310
Off Day	8:00	0.0616	−0.0285	−0.0127	0.0051	0.1692 *	0.0203	0.0102	0.0019	0.03094 *	0.0098
	10:00	0.0857	−0.0150	0.0092	−0.0117	0.1781 *	−0.0713	0.0388 *	0.0154 *	0.0350 *	0.0264
	12:00	0.0903	−0.0306	−0.0416	−0.0063	0.0838	0.0666	0.0488 *	0.0266 *	0.0428 *	0.0580 *
	14:00	0.0943	−0.0162	−0.0101	−0.0173	0.0384	−0.0100	0.0523 *	0.0175 *	0.0470 *	0.0586 *
	16:00	0.1036	−0.0426	−0.0459	−0.0117	0.0204	0.0838	0.0447 *	0.0445 *	−0.0129	0.0438
	18:00	0.0999	−0.1286	−0.0249	−0.0146	0.2333 *	−0.0714	0.0322 *	0.0346 *	0.0372 *	0.0575 *
	20:00	0.0792	0.0128	0.0255	−0.0049	−0.0979	−0.0182	0.0347 *	0.0291 *	0.0126	0.0287
	22:00	0.0757	0.0103	0.1721 *	−0.0155	−0.0161	0.0429	0.0380 *	0.0204 *	0.03133 *	0.0310
	8:00	0.0616	−0.0285	−0.0127	0.0051	0.1692 *	0.0203	0.0102	0.0019	0.03094 *	0.0098
	10:00	0.0857	−0.0150	0.0092	−0.0117	0.1781 *	−0.0713	0.0388 *	0.0154 *	0.0350 *	0.0264

* Asterisks next to numbers indicate statistically significant ($p < 0.01$).

The OLS regression results for the Long Shou Yuan station realm (residential type) are shown in Table 7. Among them, the financial POIs (V2), accommodation POIs (V5), and catering POIs (V6) show a significant positive relationship on both working days and off days, indicating that these three types of facilities are highly attractive to population activities most of the time. The medical and health POIs (V4) have a negative effect on population activity most of the time. In addition, the entertainment POIs (V1) have a positive relationship on working days most of the time compared to off days, indicating that the entertainment POIs (V1) are more attractive to population activity on working days than off days.

Table 7. The OLS regression results for the LSY station realm.

Day	Period	Explanatory Variables									
		Intercept	V1	V2	V3	V4	V5	V6	V7	V8	V9
Working Day	8:00	0.2122	0.0339	0.0773	−0.0306	−0.0352	0.0277	0.0110	0.02139 *	0.0033	−0.0165
	10:00	0.1886	0.0457	0.2109 *	−0.0055	−0.0711	0.0615 *	0.0025	0.0152	0.0168 *	0.0909 *
	12:00	0.1759	0.0938	0.1826 *	0.0113	−0.0454	0.0172	0.0290 *	−0.0054	0.0202 *	0.0772 *
	14:00	0.1638	0.0948	0.1541 *	0.0053	−0.0468	0.0287	0.0244 *	0.0069	0.0289 *	0.0953 *
	16:00	0.1673	−0.0462	0.1976 *	0.0113	−0.0677	0.0196	0.0241 *	0.0190	0.0271 *	0.0684 *
	18:00	0.1813	0.0343	0.1831 *	−0.0059	−0.0132	0.0457	0.0210 *	0.0139	0.0255 *	0.1256 *
	20:00	0.2522	0.0557	0.1148	−0.0326	0.0145	0.0445	0.0353 *	0.0105	0.0141 *	0.0442
	22:00	0.2838	0.0282	0.0704	−0.0312	−0.0741	0.0651	0.0337 *	0.0001	0.0045	0.0636 *
Off Day	8:00	0.2163	0.0116	0.0157	−0.0198	−0.0315	0.0691 *	0.0193 *	0.0048	0.0006	0.0219
	10:00	0.2671	0.0427	0.1393 *	−0.0304	−0.0085	0.0202	0.0362 *	0.0005	0.0183 *	0.0253
	12:00	0.1761	0.0472	0.0697	−0.0080	−0.0086	0.0182	0.0125	0.0110	0.0208 *	0.1236 *
	14:00	0.2429	−0.0534	0.1604 *	−0.0420	−0.0823	0.0976 *	0.0236 *	0.0186	0.02849 *	0.1069 *
	16:00	0.2327	−0.0688	0.1281 *	−0.0082	−0.0423	0.0850 *	0.0258 *	0.0187	0.0262 *	0.1048 *
	18:00	0.1927	−0.0325	0.1617 *	−0.0055	−0.0378	0.0538	0.0212 *	0.0189	0.0320 *	0.1238 *
	20:00	0.2424	0.0503	0.1234 *	−0.0414	−0.1110	0.0499	0.0265 *	0.0204	0.0099	−0.0028
	22:00	0.2876	−0.0138	0.0263	−0.0195	−0.0619	0.0685 *	0.0167	−0.0040	0.0180 *	0.0321

* Asterisks next to numbers indicate statistically significant ($p < 0.01$).

As shown in Table 8, the medical and health POIs (V4), catering POIs (V6), shopping POIs (V8), and transportation POIs (V9) in the Bei Da Jie station realm (commercial service type) have a positive relationship with population activity during most of the working days and off days. In particular, the medical and health POIs (V4) have a significant positive impact on all time periods, due to the presence of several large or comprehensive public hospitals within the Bei Da Jie station realm, and the high accessibility of the metro

makes it even more convenient for residents from other areas to come here for medical care; this indicates that quality medical resources can be more attractive to population activity. The financial POIs (V2) and the government institution POIs (V3) have a positive relationship with population activity only during specific times of the working day. It is worth mentioning that the accommodation services POIs (V5) have a positive relationship with population activity during off days, while it is mostly negative during working days. Combined with the results of the kernel density analysis of population activity, it can be found that the Bei Da Jie station realm may be visited by more outsiders on off days, thus enhancing the attractiveness of the accommodation service POIs for population activity.

Table 8. The OLS regression results for the BDJ station realm.

Day	Period	Explanatory Variables									
		Intercept	V1	V2	V3	V4	V5	V6	V7	V8	V9
Working Day	8:00	0.2220	−0.0136	−0.0030	−0.0406	0.0729 *	0.0679 *	0.0105	−0.0110	−0.0010	0.0487
	10:00	0.2239	−0.0047	0.0377	0.0112	0.1117 *	0.0466 *	0.0263 *	−0.0192	0.0075	0.0917 *
	12:00	0.2127	−0.0792	−0.0002	0.0044	0.0970 *	−0.0276	0.0360 *	0.0016	0.0027	0.0651 *
	14:00	0.1958	−0.1045	0.0357	0.0208	0.0708 *	0.0154	0.0335 *	0.0057	0.0002	0.0907 *
	16:00	0.2194	−0.0509	−0.0450	−0.0196	0.0810 *	−0.0018	0.0198 *	−0.0032	0.0147 *	0.0975 *
	18:00	0.2366	−0.0796	0.0505	−0.0301	0.0782 *	−0.0102	0.0418 *	−0.0041	0.0157 *	0.0576
	20:00	0.2680	−0.0589	−0.0552	−0.0001	0.0409	0.0098	0.0193 *	0.0157	0.0083	0.0236
	22:00	0.2596	0.0207	−0.0185	−0.0233	0.0382	0.0303	0.0013	−0.0052	0.0013	0.0267
Off Day	8:00	0.2181	0.0200	−0.0121	−0.0110	0.0856 *	0.0438	0.0154	−0.0029	−0.0035	0.0269
	10:00	0.2274	0.0912	0.0306	−0.0351	0.0696 *	0.0650 *	0.0163	0.0215	0.0075	0.1067 *
	12:00	0.2596	−0.0850	−0.0053	−0.0180	0.0808 *	0.0443	0.0295 *	−0.0135	0.0136 *	0.0403
	14:00	0.2501	−0.0883	0.0316	−0.0345	0.0621 *	0.0399	0.0286 *	−0.0179	0.0155 *	0.1182 *
	16:00	0.2547	−0.1418	0.0533	0.0093	0.0900 *	0.0444	0.0385 *	0.0057	0.0083	0.0018
	18:00	0.2448	−0.0014	0.1015 *	−0.0132	0.0453 *	0.0589 *	0.0230 *	−0.0157	0.0148 *	0.0851 *
	20:00	0.2559	0.0237	−0.0117	−0.0242	0.0612 *	0.0216	0.0239 *	−0.0245	0.0050	0.0387
	22:00	0.2532	0.0323	−0.0056	−0.0546	0.0751 *	−0.0048	0.0146	0.0155	0.0003	0.0321

* Asterisks next to numbers indicate statistically significant ($p < 0.01$).

As shown in Table 9, most of functional facilities in the Wei Yi Jie station realm (public service type) have a positive relationship with population activity, except for the entertainment POIs (V1) and government institution POIs (V3). In addition, through the field survey, we found that there are several higher education schools and educational training institutions in the Wei Yi Jie Station realm, leading to the existence of many inexpensive rental rooms, restaurants, school supply stores, courier stations, and other facilities that are closely related to campus life within the area. Therefore, accommodation POIs (V5), catering POIs (V6) and living service POIs (V7) have a strong attraction to population activities most of the time.

In terms of overall spatial relationships, the “Accommodation POIs (V5)”, “Catering POIs (V6)”, “Living POIs (V7)”, “Shopping POIs (V8)”, and “Transportation POIs (V9)” in each research station realm have positive relationships with population activity most of the time. In particular, the catering service POIs have a strong positive attraction to population activities, the reason for which can be traced back to the long-standing Xi’an food culture, where restaurants have become one of the most important places for social activities for citizens. On the other hand, the transportation facility POIs generally have a significant positive relationship with population activity from 12:00 p.m. to 6:00 p.m., indicating that people have high utilization of public transportation during this time.

Table 9. The OLS regression results for the WYJ station realm.

Day	Period	Explanatory Variables									
		Intercept	V1	V2	V3	V4	V5	V6	V7	V8	V9
Working Day	8:00	0.2272	0.0540	0.0887	0.0191	0.1261 *	0.0648 *	0.0254 *	0.0281	0.0114	0.0031
	10:00	0.2542	0.0163	0.1352 *	0.0380	0.0806	0.0210	0.0035	0.0279	0.0219	0.0187
	12:00	0.2119	−0.0144	0.0843	0.0539	0.1875 *	0.0164	0.0384 *	0.0236	0.0145	0.0649
	14:00	0.2113	−0.0143	0.1203 *	−0.0344	0.0125	0.0811 *	0.0282 *	0.0485 *	0.0034	0.1023 *
	16:00	0.2100	0.0660	0.1541 *	0.0291	0.0291	0.0222	0.0060	0.0599 *	0.0024	0.0024 *
	18:00	0.2385	−0.0506	0.1521 *	0.0488	0.1015	0.1080 *	0.0214	0.0630 *	−0.0001	0.0589
	20:00	0.2686	0.0305	0.0670	−0.0348	0.0671	0.0201	0.0501 *	0.0328	0.0215	−0.0007
	22:00	0.2649	0.0652	0.0894	−0.0011	0.1094	0.0229	0.0173	0.0567 *	0.0168	−0.0345
Off Day	8:00	0.1778	0.0073	0.0650	0.0156	0.1248 *	0.0349	0.0308 *	0.0101	0.0289 *	0.0072
	10:00	0.2118	0.0144	0.0294	−0.0259	0.0551	0.1529 *	0.0423 *	0.0303	0.0100	0.0342
	12:00	0.2594	−0.0079	0.0341	0.0351	0.0379	0.1212 *	0.0368 *	0.0140	0.0202	0.0713
	14:00	0.2371	−0.0140	0.0590	0.0047	0.0230	0.0484 *	0.0567 *	0.0485	0.0127	0.0166
	16:00	0.2460	−0.0535	0.0566	−0.0307	0.0885	0.0407	0.0416 *	0.0144	0.0287 *	0.1208 *
	18:00	0.2498	0.0104	0.0730	−0.0519	−0.0480	0.0581	0.0286 *	0.0316	0.0084	0.0821 *
	20:00	0.2531	0.0249	−0.0147	−0.0211	0.0859	0.0599	0.0317 *	0.0386 *	0.0256	−0.0107
	22:00	0.2595	−0.0433	−0.0293	−0.0455	0.0138	0.0720 *	0.0305 *	0.0647 *	0.0028	−0.0094

* Asterisks next to numbers indicate statistically significant ($p < 0.01$).

In addition, from a temporal perspective, the entertainment services POIs (V1) usually have a positive relationship with the population activity only in the evening. The financial services POIs (V2) generally have a positive impact on working days (excluding BDJ Station). Since the financial institutions are usually closed on off days, they have a negative impact for most of the day. Government agency POIs (V3) are generally only open to their staff, so there is a significant negative correlation for population activity within each research station realm for most of the time, whether it is a working day or an off day.

It is worth mentioning that medical and health facilities (V4) have a positive correlation with population activity most of the time, except for LSY Station. Several provincial or municipal public hospitals (e.g., Xi'an Central Hospital, the Second Affiliated Hospital of Xi'an Jiaotong University, etc.) are concentrated within the BDJ station realm, and the medical and health facilities (V4) have a significant positive attraction for population activities almost all day long. On the contrary, although there are several private clinics and community medical service centers in the LSY station realm, the POI of medical and health facilities has a negative correlation with population activity most of the time due to the lack of large public hospitals.

5. Discussion

This study investigated the spatial features of the four study station realms of Xi'an Metro Line 2 based on positioning data from Easygo applet and POI data from AutoNavi Map and further analyzed the dynamic influence relationships of functional facilities with population activities in the station realm under different time periods through OLS models.

The results of the spatial point pattern identification show the following:

1. There is a clustering of population activities within the metro station realm, especially in the areas within 500 m of the station. Consistent findings were revealed by several studies in different cities [64–66]. In addition, the peak periods of population activity in the station realm are between 7:00 and 9:00 a.m. and between 6:00 and 8:00 p.m. on working days. On the off days, the population activity is more active during the time period from 11:00 a.m. to 5:00 p.m. In Xi'an, although the proportion of public transportation trips is increasing year by year, with the metro ratio exceeding 50% in 2021 [5], urban traffic congestion is still a serious problem. Therefore, identifying changes in the active time of population activities helps city managers accurately and effectively optimize the operation time and structure of public transportation, thus alleviating problems such as traffic congestion in the city.

2. In this paper, we found that the three types of functional facilities, namely shopping services, catering services, and living services, in each study station realm exhibit the feature that their density distribution is higher when they are closer to the station. The density distribution features of other functional facilities in different types of station realms vary greatly. In fact, the development of rail transit in China started late compared to developed countries, and stations are often built in already developed urban environments [67], which also leads to the spatial development of station realms being restricted by public policies, transportation supply, station location, land use structure, etc. [68,69], making it difficult to form a high-density, mixed functional structures around stations as advocated by TOD and station-city integration models. In this paper, we summarize the spatial distribution features of various functional facilities in different types of station realms. However, the realization of diverse urban functions clustered around the station with the support of national policies and high-quality urban renewal, thus promoting comprehensive, composite, and efficient development of the station realm, remains a complex issue. The relationship between rail transit and urban functional facilities needs further research.
3. It is worth mentioning that although POI data cannot record “informal activity” facilities that are mobile and self-organized, using real-time location data and field surveys, we found the presence of night markets in some station realms, which cause population clustering at night. The existing literature shows that night markets have an impact on the economic development and quality of life of residents in a region [70]. On the one hand, night markets can provide a means of subsistence for some of the unemployed [71] and can also serve as a vehicle for a region’s unique culture and customs [72], contributing to economic development. On the other hand, the excessive lighting, noise, and waste generated by night market activities can have a negative impact on the health of suppliers as well as local residents [73,74]. Therefore, the development of a night market economy in station realms with a base of night market activities can be effective in enhancing the vitality of the area, but the resulting public safety issues should be of concern to city managers and urban researchers.

The results of the regression analysis showed the following:

1. The POI variables, such as catering, living, shopping, and transportation, showed a high positive attraction for population activities within the station realm. This indicates that these types of services and facilities will be more likely to attract activities in this area, which is also consistent with the results of the current related studies [37,75]. In particular, catering service POIs and population activity have a significant positive correlation in all four research station realms, which indicates that catering strongly attracts population activity. For city managers, focusing on developing the local food culture can effectively improve the vitality of station realms. In addition, the study found that medical and health care POIs have a more significant positive correlation with population activity in station realms with a relatively high concentration of general or public hospitals. Especially under the influence of the COVID-19 pandemic, the demand for medical resource capacity and medical service facilities has greatly increased, making the allocation of quality medical and health resources more attractive for population activity. This finding helps city managers to better optimize the allocation of public health care resources in station realms.
2. From a dynamic perspective, there are different coefficients of variation on weekdays and off days for all POI categories in different types of station realms. For example, the financial services POIs, government POIs, and accommodation services POIs in the Xing Zheng Zhong Xin station realm have a positive relationship with population activity only on working days. In the Bei Da Jie station realm, the accommodation service POI is more attractive to demographic activities on off days than on working days. In addition, transportation facilities are significantly more positively related to population activity on working days than on off days. This suggests that on working days people are more likely to take public transportation to work, school, and other

daily activities, while on off days people may be more likely to rest at home or choose to travel by private car. In conclusion, the analytical framework developed in this paper basically describes the relationship between various types of POI facilities and population activities, and these research results can help city managers understand the needs of people's daily activities in different types of station realms from a dynamic perspective, so as to improve the allocation of urban public resources more effectively.

In terms of data, unlike exploring population distribution features by using big data such as mobile phone signaling, social media, and Wi-Fi signaling technologies [25–32], this paper uses the higher precision and better timeliness of Easygo positioning data, which provides a reliable data source for researchers to identify the dynamic distribution features of population activities from a microscopic perspective. Existing studies have shown the importance of POI data for studying the spatial and temporal distribution features and mechanisms of urban population density [76]. Therefore, the real-time positioning data of Easygo and the POI data of AutoNavi Map used in this paper help to enable researchers to obtain more convincing analysis results.

However, there are still some limitations in this study, which may be a feasible direction for improvement. First, due to the lack of staff and time constraints, only four stations in Xi'an Metro Line 2 were selected for this study to conduct specific investigation and analysis. If all stations of Metro Line 2 could be investigated and studied, the spatial features of rail transit station realms would be more completely understood. In addition, the survey data in the study are not comprehensive enough to obtain data on the land use status and population flow before the completion of Metro Line 2. If the spatial features of the station realm before and after the completion of the metro can be compared and analyzed in the future, the practical application value of the research results will be further enhanced to support the development of metro station realms.

6. Conclusions

Public rail transportation is essential in people's daily travel. With the rapid development of the city metro and the increase in the frequency of people's use of stations, various urban functions that provide convenience to people's lives are gradually concentrated in the stations and the surrounding areas where passengers gather. In this context, a full understanding of the spatial features of the existing metro station realm and the influence mechanism between the two is crucial for the future urban renewal of the area as well as the planning of others. This study achieves quantitative research on the spatial distribution of population activities and urban functional facilities by combining real-time positioning data and POI data to help identify the spatial features of the station realm. By building OLS models, we further found that "catering", "living", "shopping", and "transportation" have positive relationships with population activities in metro station realms most of the time, while financial institutions and government agencies have positive relationships at specific times. Medical and health facilities in particular have stronger associations in station realms where general or public hospitals are concentrated. In addition, the regression results basically explain the phenomenon and causes of crowd gathering in time and space, which helps to better understand the characteristics and patterns of the spatial distribution of station realms and make the formulation of related strategies more effective.

Overall, research on location-based big data resources such as WeChat's Easygo applet and AutoNavi Map's POI enables researchers to clearly identify the spatiotemporal distribution status of population activities and functional facilities at the micro level and understand people's demand for urban functions from a dynamic perspective.

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Appendix A

Table A1. Definition and classification of POI data.

Serial Number	Primary Classification	Secondary Classification	Tertiary Classification
1	Entertainment	Culture Leisure and Recreation Sports and Fitness	Museums, science and technology museums, libraries, etc. Parks, playgrounds, KTV, etc. Swimming pools, badminton courts, gymnasiums, etc.
2	Financial Service	Bank Insurance Securities	Bank management, banks, credit unions, etc. Insurance management, insurance, etc. Securities management, investment, guarantee, etc.
3	Government Agency	Government Public, Prosecution, Law Taxation Social groups	Provincial, city (local), district governments, etc. Public security, public prosecutor's office, court State tax, local tax Public groups at all levels
4	Medical and Health Care	Medical institutions Epidemic Prevention and Control Health Care Rehabilitation Pharmacy	Hospitals, medical centers, clinics Epidemic prevention, medical examination Health care, rehabilitation Pharmacies, medical equipment stores
5	Accommodation Service	Hotel	Express hotels, hotels, hostels, guest houses
6	Catering Service	Chinese restaurants Foreign restaurants Fast food restaurants Teahouse Beverage stores	Local flavor restaurants, hot pot restaurants, etc. Western restaurants, foreign cuisine restaurants KFC, McDonalds, Pizza Hut, etc. Teahouses Coffee shops, cold drink stores, dessert stores, etc.
7	Living Service	Supply service office Daily life service Ticket office	Various types of bill payment points, electricity maintenance, gas maintenance, etc. Housekeeping, dry cleaners, wedding services, hairdressing, etc. Train ticket office, bus ticket office, etc.
8	Shopping	Store Flowers, pets Furniture, building materials Wholesale market	Supermarkets, shopping malls Electrical appliances, digital product stores Tobacco, wine, tea, souvenir, and clothing stores Flower or pet stores Furniture stores, building materials markets Wholesale markets
9	Transportation Service	Public Transportation Stops Transportation parking facilities Car Service	Bus stops, cab stands, public bicycle storage points, etc. Various types of parking lots Gas stations, car rentals, traffic vehicle management, etc.
10	Public Service	Public facilities	Newsstands, telephone booths, public restrooms, etc.

The "secondary" and "tertiary" classifications in the table are not fully listed.

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