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A Study on Spatial and Temporal Aggregation Patterns of Urban Population in Wuhan City based on Baidu Heat Map and POI Data

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Abstract: Advanced technologies and big data have brought new visions and methods to urban planning research. Based on the Baidu heat map and POI data of two typical days (a weekend day and a workday) in 2018, this paper analyses the spatial and temporal aggregation patterns of crowds in the urban centre of Wuhan using ArcGIS. Aggregation patterns are defined by the intensity of population activities and the places where crowds gather. In terms of time, the daily change of population aggregation intensity is studied by counting the heat value of 24 moments captured throughout the day. The results show that on rest days, people prefer to travel around noon and in the afternoon, reaching the highest peak of the day around 15:00, while on workdays, residents' activities are affected by commuting, with obvious 'morning rush hours' and 'evening rush hours'. Firstly, the spatial correlation between the density of POI distribution and the degree of population aggregation has been studied by the spatial coupling relationship between the Baidu heat map and POI data. Secondly, the index of correlation between the aggregation of different POIs and population (ICPP) are mentioned to analyse the purposes and the degrees of aggregation during weekend and workday rush hours. Based on the ICPP, we analyse activities from three aspects: the different ICPPs between the workday and the weekend; the different ICPPs between the morning, afternoon and evening; and the different ICPPs among different POIs.

1. INTRODUCTION

1.1 Research Background and Significance

Since opening up and establishing reform, China has experienced profound social and economic changes while urban space is in the process of continuous expansion and reconstruction. These changes also invite some urban problems such as traffic congestion, dislocation of working and living space, and an imbalance of supply and demand. Spatial-temporal activity is an important perspective for understanding residents' activity patterns, as well as their daily needs ([Moudon et al., 2005](#); [Recker, Duan, & Wang,](#)

2008; [Hess, 2001](#); [Schwanen, Dijst, & Dieleman, 2004](#); [Hertkorn & Kracht, 2002](#); [Eom & Suzuki, 2019](#)). Spatial structures and the spatial distribution of urban populations thereby interact; excessive population agglomeration and uneven spatial distribution are significant issues in China ([Gao, Z. et al., 2019](#)). On the one hand, studying the spatial-temporal aggregation patterns of the population on an urban scale can provide urban planners and managers with information regarding the constraints and dynamic factors of people's daily activities, which allows them to understand the personalised needs of residents more deeply so as to make urban planning more realistic, social management more engaged, and the service for residents friendlier. On the other hand, it provides a quantitative research basis for forecasting traffic demand, spatial planning of urban and rural areas, evaluating plans, etc. The existing research on population aggregation includes two categories: some study the urban spatial network structure from the perspective of population mobility ([Pan & Lai, 2019](#)); others quantify the population aggregation based on traditional data to analyse and predict factors such as economic and regional development ([Piao et al., 2011](#)). At present, the emergence of new data such as the Baidu heat map makes possible the study of microcosmic and dynamic spatial-temporal aggregation patterns in the population.

1.2 Related Research Based on Baidu Heat Map Data

With the development and application of Location Aware Devices (LAD) and Location Based Services (LBS), the digital footprint is convenient for effectively displaying the track of urban population flow and the state of spatial and temporal agglomeration, which addresses the shortcomings of traditional urban research and spatial planning ([Joh, Arentze, & Hofman, 2002](#)). Based on the location data of mobile phone users on an LBS platform, the Baidu heat map, a visual application launched by the Baidu Company, is a kind of image data that reflects the distribution, density and trend of dynamic changes, represented by different colours and levels of brightness ([Li, J et al., 2019](#)). The geographical location-based big data represented by the Baidu heat map provides an unprecedented perspective for urban researchers, enabling individuals to use a dynamic approach to managing urban crowd activities and the use of urban space ([Gao, S. et al., 2013](#); [Kang et al., 2012](#)). Current research on LBS data, including the Baidu heat map, focuses on the distribution of urban occupational and residential space, the temporal and spatial patterns of population activities and the identification of urban centres ([Ratti et al., 2006](#); [Rekimoto, Miyaki, & Ishizawa, 2007](#); [Zhao, Lv, & De Roo, 2011](#); [Reades, Calabrese, & Ratti, 2009](#)) There are also some related studies that combine Baidu's heat map data with traditional data ([He, Dang, & Zhang, 2017](#)).

1.3 Related Research Based on POI Data

POI data refers to certain geographical entities that are closely related to people's lives, such as schools, banks, supermarkets, etc. ([Krösche & Boll, 2005](#)). Most of the existing POI-based research focuses on the identification of urban functional areas, analysis of land use and the optimization of spatial structures ([Cai, Huang, & Song, 2017](#); [Yang, Wu, & Zhang, 2018](#); [Zeng, L. & Lin, 2016](#); [Li, Juan, Long, & Dang, 2018](#)). [Chi et al. \(2016\)](#) carried out the quantitative identification of urban functional areas based on POI using two

indicators, frequency density and type proportion; [Hu et al. \(2016\)](#) mapped urban land use by using Landsat images and POI Data; Taking points of interest of commercial institutions as the research object, [Chen, Liu, and Liang \(2016\)](#) put forward a method to identify the business centres and retail format agglomeration areas, analysing the spatial distribution characteristics of different retail format agglomeration areas in Guangzhou to provide relevant references for optimising the rational allocation of commercial resources in the urban interior space.

1.4 The Research Content of This Paper

Although there are many urban studies based on Baidu heat map and POI data, few studies have combined the two to explore the correlation between population aggregation and POI distribution density. Therefore, based on the two types of data mentioned above, the spatial-temporal aggregation patterns of urban crowds are explored. Since the heat map can dynamically express the spatial and temporal aggregation of people, we attempt to study the aggregation activity of crowds based on this data; POI, as the main factor attracting people to gather, accurately represents the distribution of urban material resources, while distribution patterns vary from type to type. Since the rhythm of population activities on workdays is always homogenized while on weekends it is diversiform ([Zhang et al., 2016](#)), from the perspective of the differences in population activities between workdays and on the weekend, we conduct the research based on the following three aspects: the intensity of population activity temporally and spatially; spatial coupling analysis between population agglomeration degree and POI distribution density; and the aggregation characteristics of the population around various POIs. The proportion of high agglomeration areas relates to the intensity of population activity. The coupling analysis utilises the same hexagonal grid. The ICPPs indicate the index of correlation between the aggregation of different POIs and the population; the different ICPPs stand for the various characteristics of population activities for which three aspects are analysed in detail: the different ICPPs between the workday and the weekend; the different ICPPs between the morning, afternoon and evening; and the different ICPPs among different POIs.

2. STUDY AREA, DATA AND METHODOLOGY

2.1 Study Area

As the capital of Hubei Province and the core city of the Yangtze River economic belt, Wuhan has a unique pattern of 'three towns', which is different from other big cities ([Zeng, C. et al., 2019](#)). According to its master plan, Wuhan is divided into a central activity area, city sub-centre, new town centre and group centre. This study selects the main urban area, about 2,104.9 km² of Wuhan, as the research area, involving the central activity area and ten city sub-centres including Jiangnanwan, Sixin, Nanhu, Luxiang, Yangchun Lake, Songjiagang, Wuhu, Shenjiaji, Zhuankou and Baoxie, as well as the four new town centres of Wujiashan, Sino-French Eco-City, Zhifang and Yangluo.

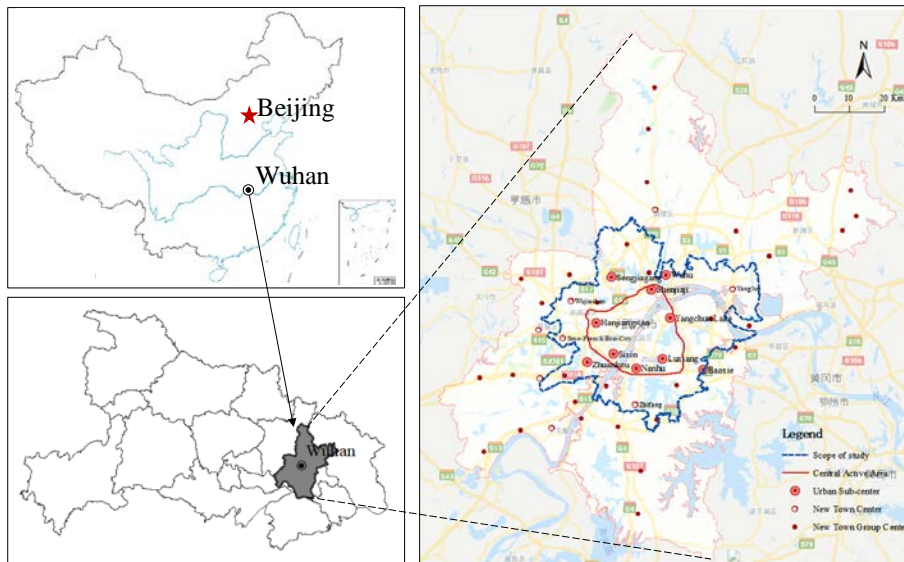


Figure 1. Study Area

2.2 Data

This research is based on the Baidu heat map and POI data. For our research, we define the data of July 8, 2018 (Sunday) as the weekend and the data of July 9, 2018 (Monday) as a workday. According to the investigation of relevant data, no extreme weather, holidays or special events occurred over these two days. Furthermore, the selected Sunday and Monday are two consecutive days, which reduces the possibility of changes caused by other factors. From 7:00 to 24:00, we extract the Baidu heat map data every 40 minutes for a daily total of 24 maps obtained during the research. The total number of 2018 POI data points contains 13 categories, including dining venues, scenic spots, corporate enterprises, shopping venues, transportation facilities, finance and banking, scientific and educational cultural services, commercial residences, life services, sport and leisure services, medical insurance services, government and social organisations, and accommodation services.

2.3 Methodology

The methods for data conversion and assignment, Kernel Density Estimation (KDE), data gridding and Pearson correlation, are integrated and applied.

2.3.1 Data conversion and assignment

This method was used for processing the 48 heat maps. Firstly, since the Baidu heat map has no coordinate information, it requires georeferencing and the inclusion of projection coordinates; secondly, because the Baidu heat map data is in PNG format, out of four channels, the Alpha channel is not disturbed by pure black and white, and is therefore easy to classify. With the Alpha channel loaded, values are classified by the natural breakpoint method: the higher the value, the greater the population density and the higher the degree of agglomeration. The agglomeration degree is divided into five levels by the reclassification tool, which are defined as non-

agglomeration areas, less agglomeration areas, general agglomeration areas, moderate agglomeration areas and high agglomeration areas.

2.3.2 Kernel Density Estimation (KDE)

Regarding expression methods for points of interest, the Kernel Density method (KDE) is superior to other density expression methods (such as quadrat density, Voronoi map density, etc.) because it considers the location effect of the first law of geography (Okabe, Satoh, & Sugihara, 2009; Borroso & Porceddu, 2009; Chu et al., 2012). All kinds of geographic events may occur at any spatial location, and the probability of occurrence also varies from location to location. KDE analysis is a method for characterising the probability of geographic event occurrence in a particular region. The calculation formula is shown below.

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

Formula: $f(x)$ is the kernel function; h is the bandwidth that is the radius of the circle; $x-x_i$ represents the distance from the estimated point to the output grid (Flahaut et al., 2003).

The KDE method is used to analyse the POI data, while the complete map of POI spatial distribution is obtained.

2.3.3 Data gridding

The grid used in data gridding consists of many shapes, such as squares, triangles and hexagons. Because of the hexagon's more abundant topological relationships (Gao, S. et al., 2017), it was selected as the grid shape. The population density and POI distribution density maps are processed by hexagonal gridding and the Pearson correlation test using SPSS software. The same statistical unit is also convenient for studying the spatial coupling of the two maps.

2.3.4 Pearson correlation analysis

Correlation analysis reflects the correlation between POI distribution density and population activity intensity, in which the correlation coefficient is used to measure the degree of correlation between the two variables. The larger the correlation coefficient, the stronger the correlation. The range of its value is [-1,1] (Bakillah et al., 2014; Yao et al., 2017). The calculation formula is shown below.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

Formula: x_i is the observation value from the x sample; y_i is the observation value from the y sample; \bar{x} and \bar{y} are the average values of each sample, respectively. When $r > 0$, the two variables are positively correlated; when $r < 0$, the two variables are negatively correlated; when $r = 0$, the two variables are irrelevant. And when $0.8 \leq |r| \leq 1$, there is a strong correlation between the two variables; when $0.6 \leq |r| \leq 0.8$, the two variables are very strongly correlated; when $0.4 \leq |r| \leq 0.6$, they are moderately related; when $0.2 \leq |r| \leq 0.4$, they are weakly correlated; and when $|r| \leq 0.2$, they are very weakly correlated or uncorrelated (Cheng et al., 2019).

3. THE TEMPORAL AND SPATIAL CHANGES OF POPULATION ACTIVITY INTENSITY

3.1 Temporal Changes in Population Activity Intensity

The proportion of high agglomeration areas is used to indicate the intensity of population activity. The proportion of high agglomeration areas was counted at 24 time points on a workday and during the weekend, namely, information regarding change in the intensity of population activity over one day was obtained.

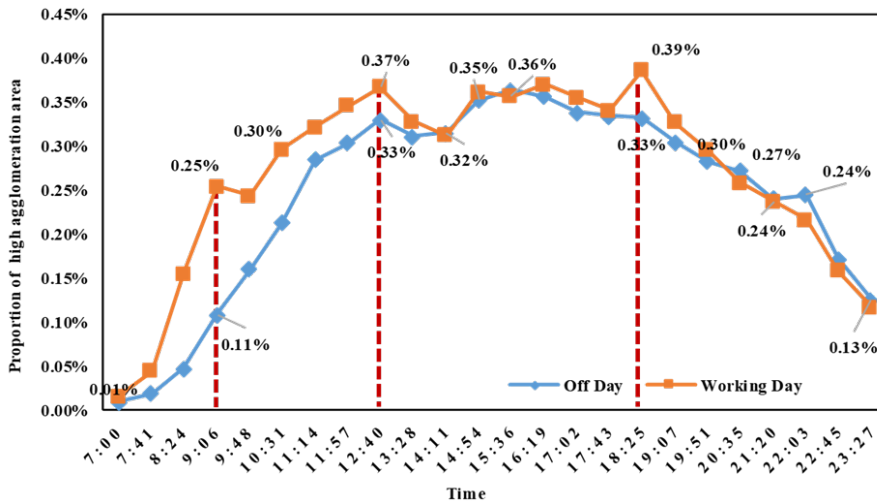


Figure 2. Changes of area proportion of high agglomeration area

Figure 2 presents that the intensity of population activity on the weekend increases slowly at first, fluctuates over a small range, and then gradually decreases. At 7:00 the intensity of population activity is at its lowest in a single day. The activity intensity then increases continuously and reaches the first peak around 12:00. The proportion of agglomeration areas then shows a specific downward trend, possibly a result of activities such as people having lunch or taking a break at home. By around 15:00, it reaches the peak of activity intensity in a day, indicating that more people choose to travel in the afternoon on weekends. High-intensity activities are maintained from 12:00 to around 18:00, after which the area of agglomeration begins to decline.

On workdays, the intensity of population activity increases rapidly at first, then fluctuates for a longer period, increases gradually, and then slowly declines. At 7:00 in the morning, when the intensity of population activity is at its lowest in a day, the activity intensity increases continuously, reaching the first peak around 9:00, reflecting the phenomenon of the early peak of commuter group travel; it then shows a specific downward trend over a short period of time, which begins to rise around 10:00; at 12:00, it reaches the second peak after which the area of agglomeration strongly fluctuates and remains high. Approaching 18:00, it reaches the highest peak of the day, signalling the main gathering time for workers returning from work and students leaving school, with the appearance of an evening peak. After this time, the activity intensity continues to decrease.

Comparing the changes in agglomeration area across two days, both reach the travel peak at around 12:00. Further, the intensity of activity and the fluctuation pattern between 13:28 and 17:43 on the weekend are the same as

those on a workday. Comparing the differences between the two, the activity intensity of a workday is always greater than that of the weekend before 14:00, while the gathering intensity of the evening peak is also obviously higher than on the weekend; the activity intensity of the population on the weekend reaches its height at about 15:30, while that of the workday reaches its highest at about 18:30; the activity intensity of a rest day is slightly higher than that of a workday only at around 22:00. It can be inferred that population activities on weekdays are mainly subject to daily commuting to work and school, which demonstrates an obvious orientation towards work; population activities on rest days are freer, and people are more willing to choose to travel at noon and in the afternoon.

3.2 Spatial Changes of Population Activity Intensity

The distributions of five levels of agglomeration degree during the working day and weekend also consist of some differences.

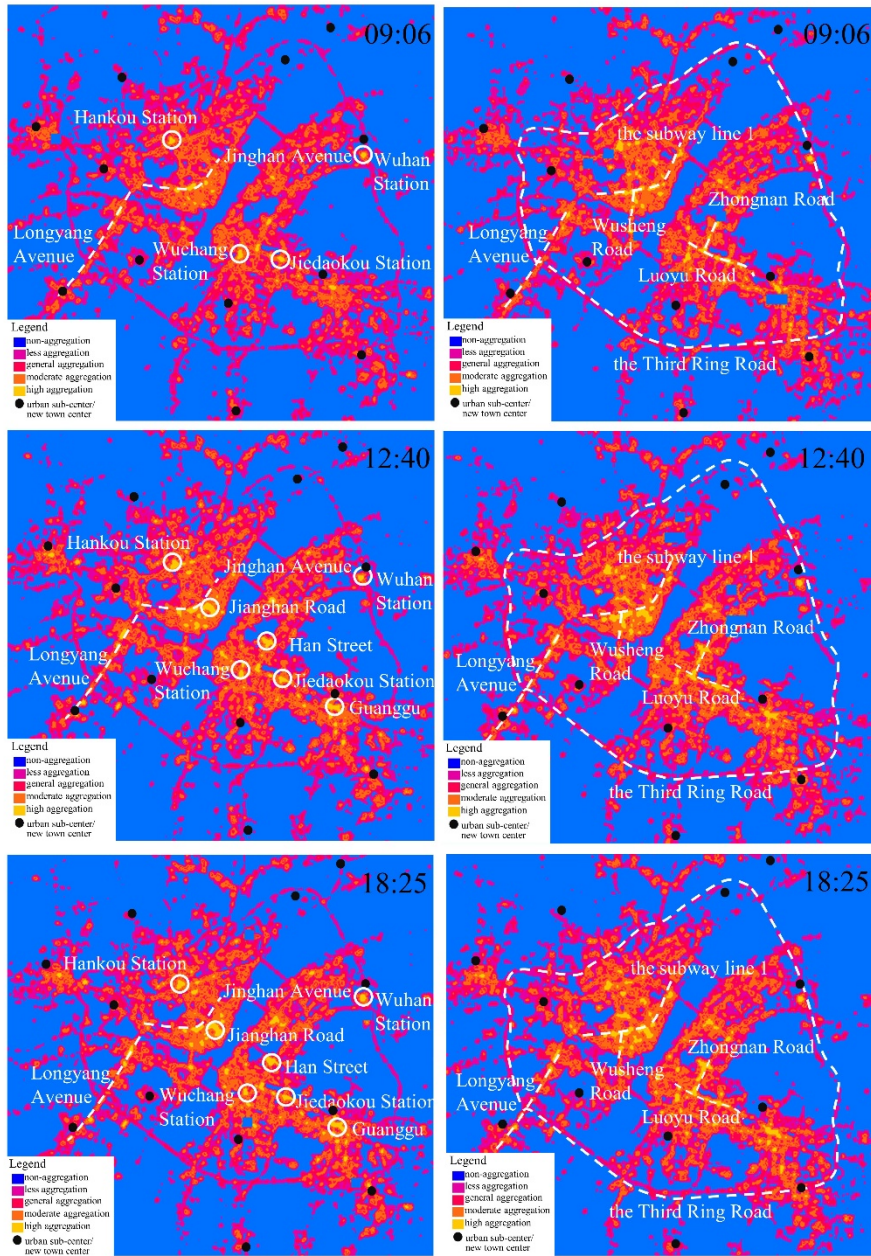


Figure 3. Changes of the proportion of high agglomeration area on weekend (left)/working day (right)

In Figure 3, the distribution of high population agglomeration areas on rest days is relatively sparse overall. The population first gathered near Jiefang Avenue, Jingshan Avenue, Longyang Avenue, Hankou Station, Wuchang Station and Jiedaokou Station. The areas of high population agglomeration expand further at noon, especially in the central activity zone of Hankou. The patches of agglomeration thus remain steady in the afternoon; the area of high agglomeration on workdays is larger and shows a linear trend of development, especially in the Subway Line 1 in Hankou district, the Third Ring Road in Hanyang district, Luoyu Road, Zhongnan Road and approaching Optical Valley in Wuchang district, which indicates that workday congestion on these roads is relatively serious.

In terms of the population aggregation of sub-centres and new town centres, the master plan's urban centres in the north of the city, such as

Shenjiagi, Wuhu and Songjiang, are unattractive. The population distribution of the centres in the southwest of the city such as Wujiashan, Zhuankou, Sixin, Nanhu and Zhifang is not ideal, considering their lack of a sustained high-density aggregation patch. Driven by certain factors such as transport stations, industry, economy and employment opportunity, there are obvious agglomeration patches in another planning centres; for example, the Yangchun Lake area influenced by Wuhan Station and the Luxiang area influenced by the Optical Valley are both core sub-centre attractions.

4. SPATIAL CORRELATION BETWEEN POPULATION AGGLOMERATION DEGREE AND POI DISTRIBUTION DENSITY

4.1 Comparison of the Distribution Map of Population Density and POI Kernel Density

The two-day average population activity intensity was obtained by superimposing 48 heat maps at each time of the workday and weekend. The POI data was analysed using the Kernel Density method, and the spatial distribution map of POI density was thus obtained. The data was then applied to the grid based on the same hexagonal shape. The natural breakpoint method was used to classify the intensity of population activity and the agglomeration density of POI into five levels. The darker the colours, the higher the potential population quantity and supply of service facilities.

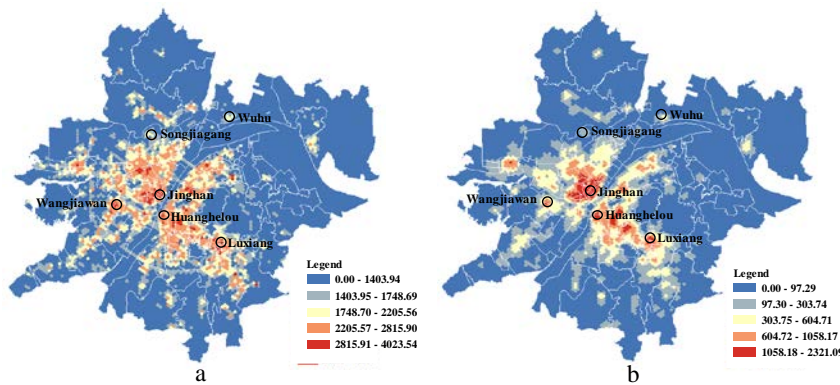


Figure 4. Distribution map of density: (a) population; (b) POI

As Figure 4 shows, both distribution maps of population density and POI density show a decreasing trend from the centre to the surrounding areas. In the central active area, the high value points of the two factors are clustered in the Jiangnan area and the riverside area of Hankou, are distributed in patches in the Huanghelou and Luxiang area of Wuchang district, and also appear sporadically in the sub-central area of Wangjiawan. Outside the central active area, new town centres such as Wuhu, Songjiagang and Wujiashan also have distributed high-to-medium values. The difference is that the distribution of population activity intensity shows a trend in linear expansion, while that of POI is relatively compact, which may be affected by the floating population on the road.

4.2 Correlation Test

The two collections of data were applied based on the same hexagonal grid, in which every grid has two values consisting of population distribution density and POI distribution density. The correlation index between population agglomeration degree and POI distribution density (ICPP) were obtained through Pearson analysis.

Table 1. Descriptive Statistics

	Mean	Std. Deviation	N
The Kernel Density of POI	1.44	0.846	7445
population activity intensity	1.55	0.988	7445

Table 2. Correlation

		Mean	Std. Deviation
The Kernel Density of POI	Pearson Correlation	1	0.826
	Sig. (2-tailed)		0.000
	N	7445	7445
Population Activity Intensity	Pearson Correlation	0.826	1
	Sig. (2-tailed)	0.000	
	N	7445	7445

Pearson analysis showed $P = 0.000 < 0.01$, indicating a statistical significance; the ICPP is 0.826, greater than 0.8, indicating a high correlation between the two.

4.3 Coupling Analysis

To further explore the spatial matching between population activity intensity and POI distribution, the average population activity data and the Kernel Density of POI data are normalised to facilitate the processing of the relationship between them, and are divided into high, middle and low levels according to the natural breakpoint method. Referring to existing analysis methods for spatial matching patterns (Liu, Luo, & Li, 2012), POI agglomeration level and population activity intensity level were assigned, respectively. Between them, the POI Kernel Density grade is assigned to 30, 20 and 10 in turn from high to low, in which the higher the value, the higher the supply potential of facilities; the three grades of population activity intensity are assigned to 3, 2 and 1, respectively from high to low in which the higher the value, the higher the intensity. Next, the matching matrix in Table 3 is obtained with the raster subtraction operation in map algebra. Finally, the spatial coupling relationship between population density distribution and the Kernel Density of POI is visualized using the method of two-factor combination mapping, from which the spatial coupling map between POI Kernel Density and population density is obtained.

Table 3. Coupling table (POI-Population)

POI/Population grades	3	2	1
30	High- High (27)	High-Middle (28)	High-Low (29)
20	Middle-High(17)	Middle-Middle (18)	Middle-Low (19)
10	Low-High (7)	Low-Middle (8)	Low-Low (9)

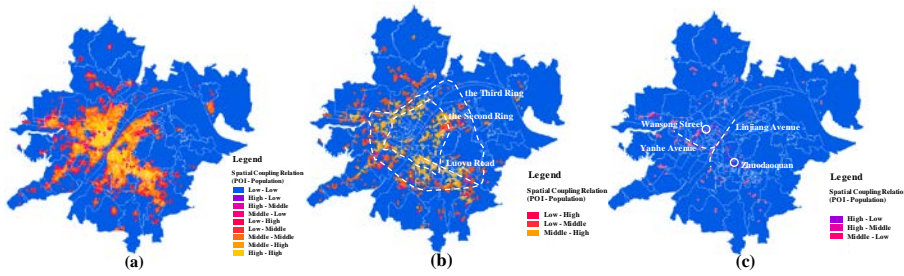


Figure 5. Coupling of POI Kernel Density and Population Density: (a) Global Coupling; (b) POI Kernel Density Value lower than Population Density Value; (c) POI Kernel Density Value higher than Population Density Value

Table 4. Spatial coupling relationship between POI data and Population

Spatial Coupling Relation (POI-Population)	Proportion (%)	Matching Results	Proportion (%)
Low-Low	76.95	Perfect Match	85.80
Middle-Middle	6.07		
High-High	2.78		
Low-Middle	6.55	Population Higher than POI	12.24
Middle-High	4.92		
Low-High	0.77		
Middle-Low	1.69	POI Higher than Population	1.96
High-Middle	0.26		
High-Low	0.01		

As can be seen from Figure 5 and Table 4, the areas with perfect match (high-high, medium-medium, low-low) account for the largest proportion, 85.8%, while the circular structure generally diffuses from the central area to the outside. Among them, areas with a high-high coupling relationship are mostly distributed in the central active area; the areas with a middle-middle coupling relationship are mostly distributed in the periphery of high-high coupling areas; and most areas with an outward coupling relationship have almost reached a low-low coupling relationship. This indicates that the spatial distribution of the two factors presents a regular pattern of higher density in the middle and sparser surroundings.

The area in which the POI Kernel Density Value is lower than the Population Density Value is the second largest, of which most are surrounded by the edge of the central active area, showing a decreasing trend from the centre to the surrounding area, which indicates the lack of resource allocation in the area between the city centre and the new town centre. Around Wuhan Station, in the inner margin of the central active area, areas with the higher population density of middle-high and low-middle have a tendency to develop into blocks; in the Hankou and Hanyang districts, in the margin of the central active area, the distribution pattern runs along the Second Ring Line and the Third Ring Line, while in the Wuchang district, the distribution mainly extends along the Luoyu Road until it touches the Third Ring Line, indicating a continuous flow of people on the section of the road.

The areas with higher POI density, scattered in the form of dots in the urban central area, as well as in the sub-centres and new town centres, account for the smallest proportion. The distribution density of POI in Linjiang Avenue, Yanhe Avenue and Wansong Street within the Second Ring Line is relatively high, which indicates that the infrastructural configuration of this area is relatively ideal.

5. THE AGGREGATION CHARACTERISTICS OF POPULATIONS AROUND VARIOUS POIS

It has been proven that the correlation degree between POI density and the intensity of population activity can reflect the dynamic degree of urban facilities in space by using the correlation analysis method (Li, J et al., 2019). It is also confirmed that there is an obvious correlation between population activity intensity and POI distribution density. However, different types of POI have different spatial distribution characteristics, and their level of attraction varies from POI to POI. Therefore, the aggregation characteristics of population around various POIs in time, based on different ICPPs in a time series will be explored. The higher the ICPP value between a certain kind of POI and population aggregation degree, the higher the likelihood of population aggregation.

From previous studies, we find that the greatest difference in population travel intensity between the weekend and a workday occurs at about 9:06, 12:40 and 18:25, which are all peak points in a single day. Therefore, we selected these three time points as experimental cases representing the morning, noon and afternoon. According to the Pearson correlation between POI distribution density and population distribution intensity at three time points of a workday and rest day, we found that $p = 0.000$, which indicates a statistical significance. Meanwhile, the coefficient of the correlation (ICPP) will be discussed in the following passage.

According to the *Athens Charter*, cities have four functions: living, working, transportation and recreation. Thirteen categories of POIs were chosen to be analysed: dining venue, scenic spot, corporate enterprise, shopping venue, transportation facilities, finance and banking, scientific and educational cultural service, commercial residence, life service, sport and leisure service, medical insurance service, government and social organization, and accommodation service. To more easily explore the aggregation characteristics of populations, we can summarise the 13 POIs into these four functions, as shown in *Table 5*.

Table 5. Functional classification of 13 POIs

Functions	POI Categories	Abbreviation
Living	Commercial Residence	CR
	Life Service	LS
	Medical Insurance	MI
	Accommodation Service	AS
Working	Corporate Enterprise	CE
	Finance and Banking	FB
	Government and Social organization	GS
Transportation	Transportation Facilities	TF
Recreation	Dining Venue	DV
	Scenic Spot	SS
	Shopping Venue	SV
	Scientific and Educational Cultural Service	SE
	Sport and Leisure Service	SL

5.1 Different ICPPs between the Workday and the Weekend

Table 6. ICPP values of all categories during different times

CATEGORIES	WEEKEND			WORKDAY		
	9:06	12:40	18:25	9:06	12:40	18:25

SV	0.818	0.827	0.807	0.771	0.801	0.823
DV	0.811	0.823	0.807	0.767	0.807	0.828
SL	0.792	0.803	0.785	0.746	0.790	0.810
LS	0.786	0.793	0.779	0.736	0.768	0.796
TF	0.782	0.795	0.775	0.776	0.799	0.816
MI	0.748	0.738	0.720	0.702	0.717	0.742
FB	0.746	0.755	0.732	0.735	0.757	0.779
SE	0.732	0.749	0.723	0.707	0.740	0.760
CR	0.731	0.740	0.715	0.700	0.743	0.749
GS	0.724	0.727	0.712	0.713	0.723	0.739
CE	0.662	0.677	0.663	0.693	0.714	0.713
AS	0.644	0.658	0.647	0.607	0.656	0.660
SS	0.267	0.288	0.278	0.263	0.269	0.284

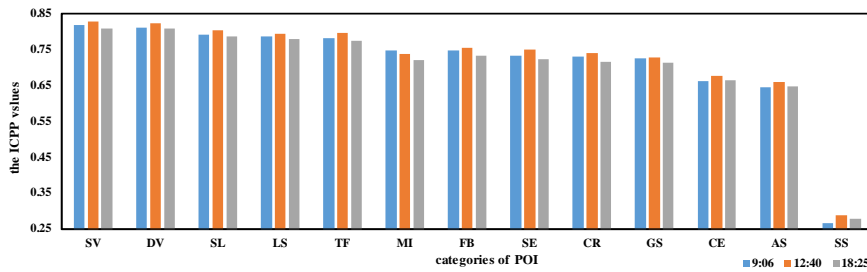


Figure 6. ICPPs on the weekend

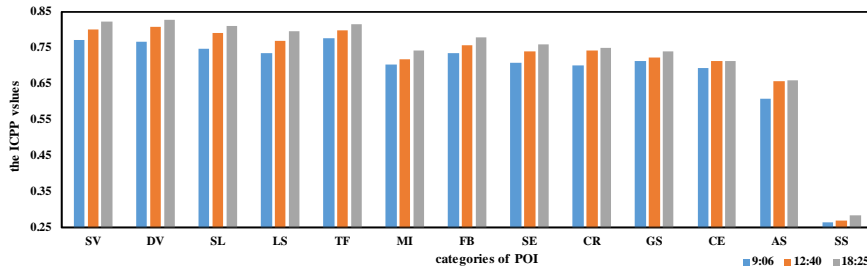


Figure 7. ICPPs on a workday

In terms of ICPP values in *Table 6*, the distributions of recreation sites, such as SV and DV, have the strongest correlation with population agglomeration, while the distributions of LS, TF, MI, FB, SE, CR and GS are also strongly correlated. Further, considering that the amount of SS distributions is very small, there is a weak correlation.

Figure 6 and *Figure 7* indicate that on the rest day, except for the Medical Insurance Service (MI), the ICPP value is the highest in the afternoon. In addition, the difference in people's purpose for travel over one day is small. On the workday, the ICPP value always shows an increasing trend from morning to afternoon, while the difference in travel purpose in the morning, noon and afternoon is relatively greater than that on the weekend.

5.2 Different ICPPs between the Morning, Noon and Afternoon

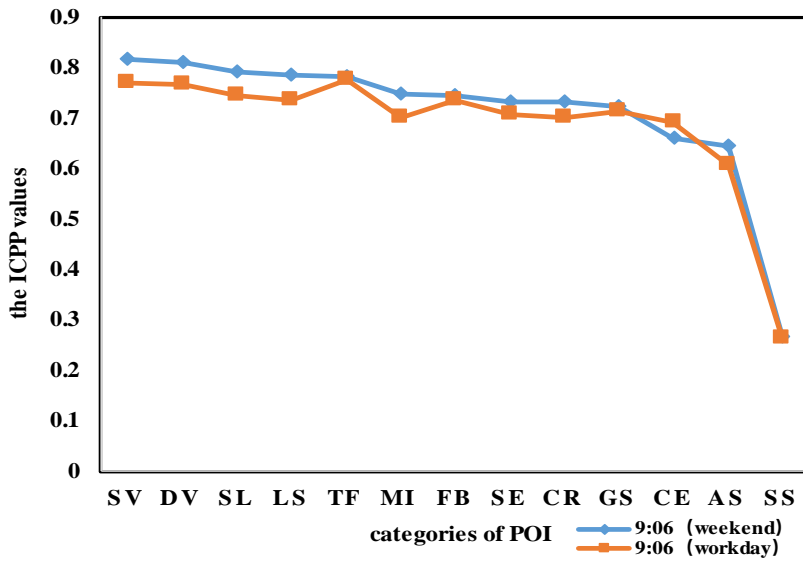


Figure 8. ICPPs at 9:06

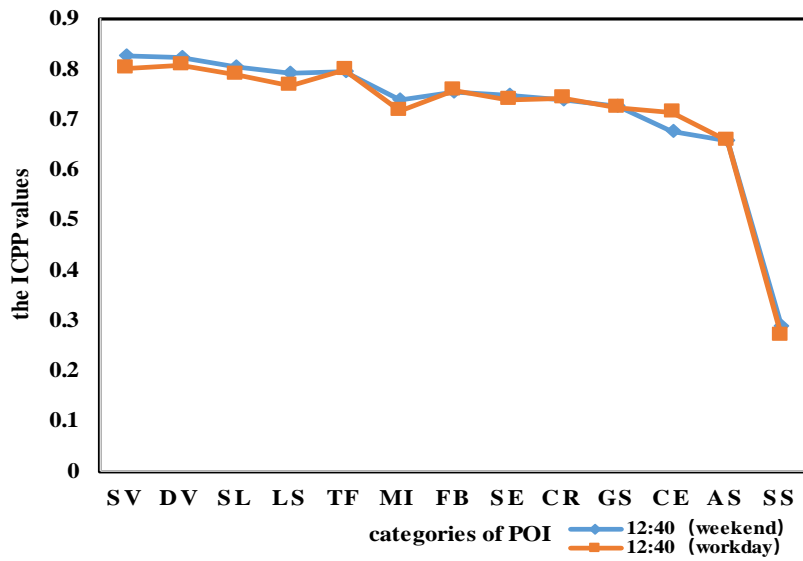


Figure 9. ICPPs at 12:40

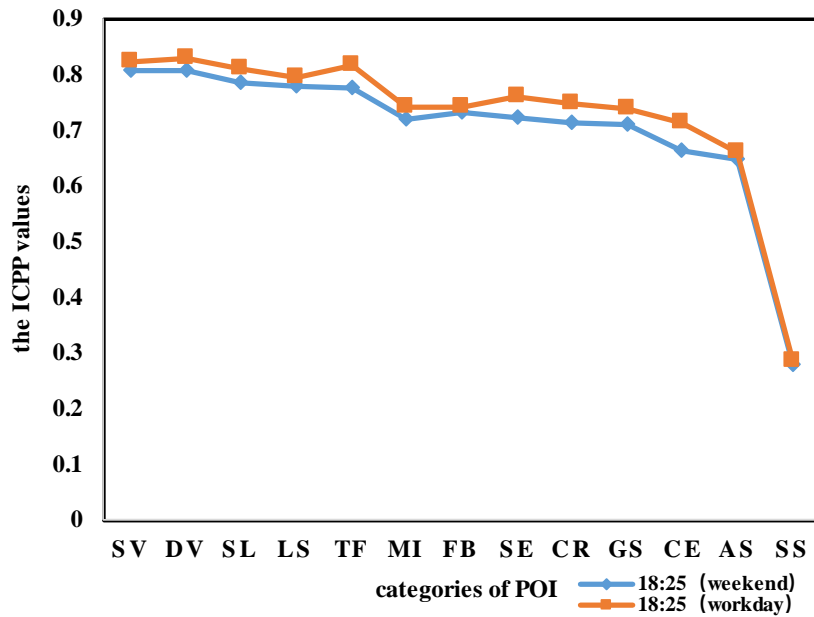


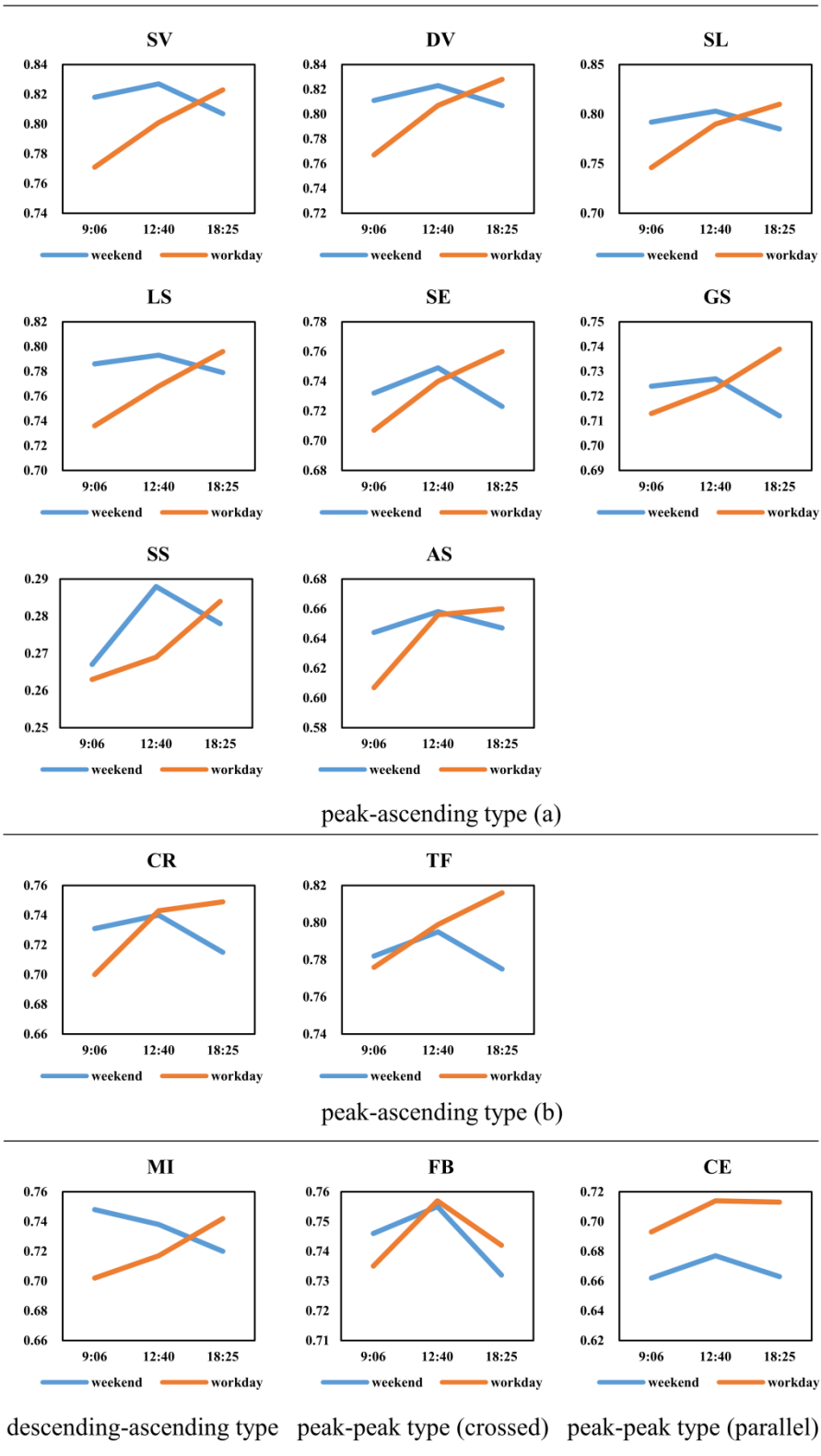
Figure 10. ICPPs at 18:25

Figure 8-10 show that on a weekend morning, the aggregation degrees around various facilities are greater than that on workdays, and that those of recreation places (SV, DV and SL) are the highest on weekends. The ICPP values of various facilities on workdays generally decline, although the population aggregation degree of transportation (TF) and workplaces (FB, GS and CE) remains unchanged, or even increases. At noon, the aggregation degree of workplaces (CE) on a workday is obviously higher than that on a rest day. In the afternoon of a workday, the aggregation degrees of all facilities are greater than those on the rest day. In addition, the attractions of all kinds of POIs are almost the same, in which commercial leisure locations (SV, DV) consistently draw strong attraction throughout the two days. On rest days, SL is relatively attractive, while on workdays, TF becomes the most significant place for populations to gather. This demonstrates that transportation facilities are attractive to people on workdays, while entertainment facilities are more evidently attractive to people on rest days.

5.3 Different ICPPs among Different POIs

There are three types of crowd gathering patterns over the course of one day: peak type, ascending type and descending type. The corresponding patterns on workdays and rest days can be summarised as five types, as Table 7 shows: peak-ascending type (a), peak-ascending type (b), descending-ascending type, peak-peak type (crossed) and peak-peak type (parallel).

Table 7. Five types of corresponding patterns on workdays and rest days



Peak-ascending type (a) means that the gathering situation on the weekend rises first and then decreases, while that on a workday gradually rises, and that ICPP values in the morning and at noon on rest days are higher than those on workdays. The POIs of the recreation and living functions, such as SV, DV, SL, LS, SE, SS and AS, belong to this type. It

shows that on the rest day, people are more willing to visit restaurants, as well as shopping, living, science and education-related locations at noon, while on the workday, people are more willing to go out later, typically after work.

Peak-ascending type (b) is fundamentally consistent with the dynamic change of peak-ascending (a), however in the morning of the rest day, ICPPs are higher than those on a workday. The POI categories of this type include living places (CR) and transportation (TF). It shows that in the morning residential areas are more attractive on weekends than those on workdays, while in the afternoon people are more willing to go home during workdays, making residential areas and transportation more attractive.

Descending-ascending type demonstrates that weekend ICPP values decline gradually, while those of the workday increase gradually throughout the day. Out of all categories, only MI belongs to this type. It can thus be inferred that on weekends people are willing to visit the hospital as early as possible in the day, while on workdays, people are more willing to visit the hospital after work.

Peak-peak type (crossed): The daily aggregation degree of weekends and workdays first increases, and then decreases. Out of all categories, only FB belongs to this type. It demonstrates that people prefer to visit financial and banking locations at noon, regardless of whether it is a workday or weekend.

Peak-peak type (parallel): The dynamic change in aggregation of this type is fundamentally consistent with that of peak-peak type (crossed), although the aggregation degree of workdays over the course of one day is higher than that of rest days. Out of all categories, only CE belongs to this type. It is also reasonable that the daily attraction to workplaces is higher on workdays than on rest days.

6. CONCLUSIONS AND LIMITATIONS

Based on the Baidu heat map and POI data, this research analyses the spatial and temporal characteristics of travel patterns of populations in the central city of Wuhan.

The results show that in terms of time, whether on workdays or the weekend, the minimum agglomeration is in the morning, followed by the afternoon, with the greatest vitality at noon. On the weekend, the duration of crowd agglomeration is shorter than that of the workday, with lag and delay factors. While the residents are free to move around, they are more likely to wake up later in the morning on weekends, meaning that the first activity peak does not appear until 12:30, and will reach the highest point by 15:30 on the weekend. Since the time of people's workday activities is controlled by cyclical activities such as commuting to work and going to school, the agglomeration degree shows significant peaks at about 9:00 and 18:00.

Spatially, the distribution of population aggregation fundamentally demonstrates the characteristics of multiple and clustered aggregation in the centre, with diffusion along the outside road network. On workdays and rest days, areas of high agglomeration generally appear in the same place, and are concentrated around central active areas such as Jiefang Avenue, Jinghan Avenue, Longyang Avenue, Hankou Station, Wuchang Station and Jiedaokou station. In the periphery of the central activity area, there is an imbalance in the development of planning centres. The planning centres on the north side have no clear attraction to the population, while those driven by transport stations or employment opportunities, such as the Yangchun

Lake and Luxiang centres, have steady attraction. Comparing activity differences between the two days, the gathering area is more compact on rest days, while on workdays it is relatively divergent, with a trend of spreading along Second Ring Road and Louyu Road, indicating that congestion on workdays is more serious.

In terms of the purpose of population aggregation, the distributions of commercial leisure locations consistently have the strongest correlation with population agglomeration degree, while scenic spots consistently have the weakest correlation compared with other categories; transportation facilities have obvious attraction to people on workdays, while entertainment facilities have obvious attraction to people on rest days. For residential function locations, rest day mornings and workday nights are more attractive; for most recreation and living locations, people prefer to gather around after noon on rest days, or after a day's work on workdays; while hospitals and financial and banking institutions are special cases, on rest days, people prefer to visit the hospital as early as possible during the day, while on workdays, people typically visit in the afternoon. Regardless of whether it is the workday or weekend, people are more willing to visit financial and banking locations at noon.

According to the results of the previous analysis, the following suggestions are thus put forward for urban development and construction management in the future:

1. Build a reasonable and balanced system for activity space and improve the system for multi-central space development; enrich the types of activity space in the northern urban sub-centres (Shenjiaji, Wuhu and Songjiang) to make up for the lack of development power in the centres. As for the areas with weak allocation of commercial, educational and medical facilities, etc., corresponding layout strategies for facilities are proposed to strengthen the guidance and support of activity spaces.

2. According to different activity characteristics of people on workdays and the weekend, a dynamic and flexible urban management and maintenance mechanism could be established: on workdays, the maintenance of urban order during the peak period of commuting should be strengthened, while on weekends, the focused time can be adjusted to the noon and afternoon. The major objectives should be dynamically maintained from three levels: zones, routes and stations. Zones: places for commercial leisure and employment centres such as shopping venues, dining venues, sport and leisure services and Optical Valley; Routes: Luoyu Road, Zhongnan Road, Jiefang Avenue, Jinghan Avenue, Longyang Avenue, ring roads, etc. Stations: Jiedaokou Station, Wuhan Station, Wuchang Station, Hankou Station, etc.

In this paper, the Baidu heat map and POI data are used to explore the travel rhythm and purpose of crowds, while relevant suggestions are suggested for improved planning and management. Since the Baidu heat map data is unable to accurately trace individual activity, with no specific information such as age, gender, working status, etc., in the future, we therefore need to combine other multi-source data that contains information on population characteristics to study the activity patterns of different groups of people.

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