Construction of public security indicators based on characteristics of shared group behavior patterns

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Abstract

Purpose – Human group behavior is the driving force behind many complex social and economic phenomena. Few studies have integrated multi-dimensional travel patterns and city interest points to construct urban security risk indicators. This paper combines traffic data and urban alarm data to analyze the safe travel characteristics of the urban population. The research results are helpful to explore the diversity of human group behavior, grasp the temporal and spatial laws and reveal regional security risks. It provides a reference for optimizing resource deployment and group intelligence analysis in emergency management.

Design/methodology/approach – Based on the dynamics index of group behavior, this paper mines the data of large shared bikes and ride-hailing in a big city of China. We integrate the urban interest points and travel dynamic characteristics, construct the urban traffic safety index based on alarm behavior and further calculate the urban safety index.

Findings – This study found significant differences in the travel power index among ride-sharing users. There is a positive correlation between user shared bike trips and the power-law bimodal phenomenon in the logarithmic coordinate system. It is closely related to the urban public security index.

Originality/value – Based on group-shared dynamic index integrated alarm, we innovatively constructed an urban public safety index and analyzed the correlation of travel alarm behavior. The research results fully reveal the internal mechanism of the group behavior safety index and provide a valuable supplement for the police intelligence analysis.

Keywords Human behavior, Shared travel, Behavioral dynamics, Risk index, Urban public security index, Intelligence analysis

Paper type Research paper

1. Introduction

In recent years, the research on characteristics of group behavior patterns has attracted extensive attention in the academic circle of human behavior dynamics. Characteristics of group behavior patterns are highly complex and diverse, making it full of great challenges to study them (the elements of group behavior patterns mentioned here mainly focus on the behavior patterns of groups in daily life). The purpose of the study on the parts of group

behavior patterns is to establish the corresponding feature model by analyzing and mining the data related to group daily behavior. In terms of research methods, the model of group behavior research is to quantitatively analyze the episodic, memorizing and power-law distribution of group behavior through real and objective data. It follows the cycle of "data collection, feature analysis, mathematical model reappearance" data rules "without human intervention and objectively reflects the law revealed by the data.

So far, studies on model group behavior have been based on general cases, such as (Katzenbach and Smith, 2015) explaining Poisson's characteristics based on people's timely processing of E-mail. Wuchty et al. (2007) found that European mobile phone users (based on a population level) follow the long-back exponential distribution. Another example is literature (Gowers and Nielsen, 2009), based on the analysis of Chinese mobile phone users through the memory of call interval and parody research. It is found that the distribution of call time intervals obeys power-law distribution and that most human behaviors obey characteristics of strong retention and weak memory. Subsequently, a large number of practical models were put forward for statistical analysis of group characteristics of human behavior, including priority queue (Naimi and Westreich, 2014), Poisson process (Lazer et al., 2009), adaptive model (Shmueli et al., 2014), etc. In order to reveal characteristics of different traffic behavior patterns of groups, Jing et al. (2021) holds that according to the human travel distance and residence time calculated at the group level, it can be inferred that the travel distance and residence time of each individual in the group also obeys the power-law distribution.

However, some scholars have begun to study the behavior pattern based on mobile phone calls in the process of abnormal events due to characteristics of group behavior patterns in unconventional cases (Gao et al., 2014). They found that emergencies can lead to a significant increase in eyewitness social activities (making phone calls, sending text messages, etc.).

Therefore, based on the research method of human behavior dynamics, this paper analyzes the data of large-scale shared bicycles and ride-hailing sensors in Chinese metropolises. With the integration of urban points of interest, the multi-dimensional travel characteristics of group traffic passengers are mined and a multi-spatial resolution urban regional association network based on alarm behavior is constructed. Behavioral dynamics characteristics of different travel tools are discussed and the urban regional safety risk index is further analyzed.

The rest of this paper is organized as follows: in the second section, we review characteristics of human behavior, urban points of interest and their applications in traffic behavior. Section 3 gives some preliminary ideas, including related concepts and terminology. In Section 4, we will show and analyze the experimental results based on the data set of shared bikes and online car-hailing and the fusion of related alarm data sets. The first part analyzes the community attributes of a large city in China and further constructs the urban community of street safety index. In Section 5, we present our conclusions and future work.

2. Related work

2.1 Group behavior analysis

Group behavior refers to the sum of the behavior of multiple individuals under one spatio-temporal environment. These individuals may achieve a particular goal, or they may just be limited by time or space. Their actions may influence each other, or they may be independent. At first, this concept was put forward and studied by anthropologists, sociologists, biologists and psychologists. In the following decades, researchers primarily analyzed group behavior from sociology and psychology and their research results were

applied to explain behavior characteristics and patterns of humans and other groups of animals (Gowers and Nielsen, 2009). With the big data era (Naimi and Westreich, 2014), more and more computing scientists have joined group behavior research. For example, in 2009, some computing scientists headed by Professor Alex Pentland of the Massachusetts Institute of Technology put forward the concept of Computational Social Sciences (Computational Social Science) (Lazer et al., 2009), that is, to study social behavior by collecting and analyzing large amounts of data. Group behavior analysis is the focus of this discipline.

In recent years, communication technology has made relationships between people, people and other organisms closer. In contrast, data acquisition and storage technology progress makes the group target behavior data obtained by researchers more and more abundant. This stimulates the social and commercial needs of group behavior research and provides a technical guarantee and data basis for the development of group behavior research. From the perspective of business and social value, group behavior modeling and analysis technology have extensive applications, so it is highly valued in the information age. In fact, at present, there is an increasing demand for group behavior analysis technology in many fields, such as network analysis (Scott, 1988), urban planning (Burgess et al., 2017), financial management (Charles and Sguotti, 2021), biological conservation (Laughlin et al., 2014) and so on. The results of group behavior analysis are more and more widely used. In the research of virtual media information networks such as Weibo and Wechat, individual users form groups through information exchange such as the posting and forwarding of Weibo. Through the network structure (that is, user influence network) and network events (that is, user posting and other behavior) in the information network, the group behavior is modeled (Du et al., 2014). It will solve practical problems such as identifying and mining opinion leaders, discovering critical paths of information dissemination and estimating the influence of the information dissemination window (Du et al., 2013). It directly applies to network marketing (Zhang et al., 2020), public opinion analysis (Chen et al., 2020), advertising push, etc.

Group behavior analysis technology often needs to deal with massive heterogeneous data and design corresponding models and algorithms for different applications. To determine the group behavior more accurately, further reveal the diversity and correlation characteristics of regional security risks and provide a reference for the application of emergency management such as optimizing resource deployment.

2.2 Temporal characteristics of human behavior dynamics
A series of human behaviors, such as communication, mobile, shopping, social and so on, are the direct or indirect driving forces of a large number of typical complex systems, such as economic system, financial system, transportation system, social system and so on. The dynamics of human behavior, initiated by statistical physicists, is a new interdisciplinary research direction, mainly from human behavior through the quantitative statistics of many individual human behaviors and group behavior. Study its complexity in time and space, reveal hidden statistical rules and explore the mechanism of these rules. And the effects on all kinds of external systems, such as society, economy, technology and ecology.

In 2005, Barabasi's study of non-Poisson characteristics of the temporal distribution of human activities based on task priority mechanism (Brabási, 2005) and the quantitative research of spatial scale law of human movement by Brockmann et al. (2006) was published in Nature in 2006. These studies have become a historical turning point in analyzing human behavior's temporal and spatial complexity. The time characteristic of human behavior is the statistical law of time when people often engage in a specific event. Researchers tend to

Poisson distribution in studying the time characteristics of human behavior dynamics in the early years. Poisson distribution was initially being proposed and named by Poisson. Then it is widely used in the quantitative model of all kinds of human activities to describe the statistical regularity of the number of specific events within a specified range or per unit of time.

However, at present, the academic circles believe that the interval time distribution corresponding to these behaviors of different individuals has a noticeable fat tail (Wang *et al.*, 2015), which a power function can better fit, that is $p(\tau) \propto \tau - \alpha$. The research on the time characteristics of human communication behavior has also been carried out in many human empirical data. The interval time between the occurrence of communication behaviors, such as e-mail (Wang *et al.*, 2014), mobile phone text messages (Jeon and Kim, 2018), mobile phone calls (Brockmann *et al.*, 2006), financial activities (Ghosh *et al.*, 2021) and so on, all obeys the power-law distribution. This paper mainly refers to the time characteristics of behavior patterns, the power index of an interval probability distribution, etc.

2.3 Spatial characteristics of human behavior dynamics
In 2010, the Barabási research team published an article on the predictability of human behavior in Science (Song *et al.*, 2010). They studied the behavior patterns of anonymous mobile phone users. They found that human daily travel activities are highly regular and independent of distance and everyone's regular travel (distances of more than 10 kilometers) indicates that 93% of activities are predictable. Kang *et al.* (2012) analyzed the correlation between human mobility patterns and city shape using mobile phone data from 8 cities in Northeast China for nine consecutive days (5 working days, two weekends). Becker *et al.* (2013) analyzed human mobility patterns and participation in group events using mobile phone data from Los Angeles, San Francisco and New York from April 1 to June 30, 2011. Csáji *et al.* (2012) analyzed human mobility patterns using mobile phone data of 100000 anonymous users in Portugal for 15 months and proposed a variety of evaluation indicators. The main statistical indicators of spatial pattern analysis include: single-step displacement (Li *et al.*, 2008), gyration radius (Ma *et al.*, 2015), convex hull diameter (Csáji *et al.*, 2012), path Euclidean distance and true distance (Ali and Shah, 2008), spatial location access frequency and ranking (Csáji *et al.*, 2012), mobile pattern diversity (Song *et al.*, 2010), predictability (Maciel *et al.*, 2021) and so on. This paper mainly refers to the path length probability distribution power index and other indicators. To increase the comprehensibility different from previous studies, the summarizing relevant work is shown in Table 1.

3. Data
In recent years, many scholars at home and abroad have devoted themselves to group behavior analysis techniques. They have made many achievements in many fields, such as biology, medicine, finance, management, electronic information, etc. Many different branches have been derived from group behavior research for various applications. Group movement behavior analysis and trajectory inference, such as crowd activity, species migration and so on, are classical problems in group behavior analysis. The data source of the problem here is mainly based on the information network built by all kinds of sensors. The most typical ones include video surveillance networks (Ali and Shah, 2008), access control systems based on radio frequency identification technology (Wang *et al.*, 2012), wireless sensor networks (Oh, 2012), radar detection systems (Lin *et al.*, 2019) and so on. The main form of data is the detailed trajectory of each individual or the aggregate data of groups in different Spatio-temporal positions (how many individuals appear in what Spatio-temporal place). Here we use the

Characteristics of group behavior patterns	Feature definition
Social Interactions Online (Chen *et al.*, 2020)	A closer match between individuals' interests and those exhibited by the Web site should result in a stronger tie between a Web site and user
Social network analysis model (Scott, 1988)	It is argued that the concept of social network provides a powerful model for social structure and that a number of important formal methods of social network analysis can be discerned
Diffusion model (Scott, 1988)	A diffusion model is often associated with a directed graph $G = (V, E)$ and a cascade from a model is just a set of influenced nodes according to the model given a set of source nodes $S \subseteq V$
J-A Models (Shmueli *et al.*, 2014)	It not only considers the assimilation effect in the social judgment theory but also considers the situations of repulsion and neutrality
Interval time probability distribution power exponent (Wang *et al.*, 2014)	The time interval between the occurrence of two adjacent times of the same individual obeys the power law distribution
Power Exponent of Probability Distribution of Waiting Time (Wang *et al.*, 2014)	The time interval of the waiting time of the same individual obeys the power law distribution
Power Exponent of Duration Probability Distribution (Wang *et al.*, 2014)	The duration of the same event obeys a power law distribution
Intermittent coefficient (Jeon and Kim, 2018)	Quantified indicator of the time interval between events
Memory factor (Jeon and Kim, 2018)	Memory characteristics of the time interval between events
Time domain diversity index (entropy) (Jeon and Kim, 2018)	Time series predictability quantitative index
Single step displacement probability distribution power exponent (Li *et al.*, 2008)	The displacement between the coordinates of adjacent positions of an individual obeys a power law distribution
Power Exponent of Probability Distribution of Radius of Gyration (Li *et al.*, 2008)	A quantitative indicator of the distance between the individual position coordinates and the center position
Power Exponent of Probability Distribution of Convex Hull Diameter (Li *et al.*, 2008)	A quantitative indicator of the distance between the individual position coordinates and the center position
Path length probability distribution power exponent (Wang *et al.*, 2015)	The length between the individual start coordinate and the end coordinate position obeys a power law distribution
Spatial diversity index (entropy) (Wang *et al.*, 2015)	Quantitative Index of Predictability of Hotspot Spatial Sequence

Table 1.
Characteristics of
group behavior
patterns

sensor data of shared bikes and online ride-hailing in a large city in China as an example to explore the multidimensional travel characteristics of group traffic passengers.

Table 2 shows a detailed description of the data set in this paper. The data set includes online car Hailing data set, shared bicycle data set and alarm data set. As shown, the online car-hailing data set contains the ride-hailing data of December 20, 2019. The travel conditions of 158,718 ride-hailing users of different companies on that day were recorded and the total number of trips recorded was 18,287,688. Each trip record contains the departure time, arrival time and order number of the trip and the speed and starting position of each trip. Then, the shared bike data of 203,577 users from May 25 to June 1, 2017, are recorded and the total number of trips recorded is 455,411. Each travel record contains the order number of the journey, the bike number used, the departure time and the geographic location code at the time of departure. The dataset comprises shared bike data from two different companies. Last, the alarm data set is used in the 110 alarm data of a city in China. The data set records the alarm data of various cases in the city within a year.

In addition, Figure 1 shows the data set analysis of urban points of interest. With the rapid development of urban construction in China, a complex urban system has been gradually

	Data set entry	Data set value
Detailed description of the ride-hailing data set	CompanyID	9
	OrderID	158718
	DateTime	20/12/2019 00:00:00–20/12/2019 23:59:49
Detailed description of the shared bicycle data set	OrderID	455411
	UserID	203577
	BikeID	268922
	BikeType	2
	StartTime	2017–05–25 00:00:03–2017–06–01 00:00:00
Detailed description of alarm data	Time Limit	365 Days
	Location Distribution	A City in China
	Number of Alarms	About one million
	Alarm interval time memory coefficient	Memory coefficient of alarm interval time for different types of cases
	Interval coefficient of alarm interval time	Interval coefficient of alarm interval time for different types of cases

formed and the metropolitan center system has become an essential part of urban geography research. The urban center system is an organic whole that is interdependent and related to each function and scale of different service areas within the city. The traditional urban spatial analysis is through on-the-spot investigation and other methods, by a certain amount of sample law to represent the prevailing law, suitable for small-scale regional research. Nowadays, the urban spatial structure is becoming more and more complex and the shortcomings of traditional methods, such as heavy workload and intense subjectivity, are becoming increasingly prominent. With the rapid development of Internet communication technology, big data has become a new research hotspot in urban geography, which provides a new idea for urban planning problem discovery and essential data acquisition and integration. At present, there have been some research achievements in the field of big urban data, such as the use of bus card swiping data to study the occupation-residence relationship

and commuting law of first-tier urban residents and the use of big data to study urban place name information and so on. However, the research is still in its infancy and it needs to be further developed to obtain a large amount of adequate data and apply it to the actual planning.

Urban Point of interest (POI) data is a method to represent the spatial and location attributes of geographical entities by querying and downloading the location big data through the API provided by the electronic network map written by computer technology. It mainly includes geographical entities that are closely related to people's lives in most cities, such as catering services, schools, housing, shopping malls, stations, government agencies, financial institutions, etc.

4. Characteristics of group behavior patterns
Firstly, this paper extracts the feature set, including group behavior pattern feature definition, feature extraction of urban interest points and definition of related features in the police field. Then analyzing correlation and constructing safety index. The last part demonstrates behavioral characteristics of alarm and urban safety index. The details of research methods have been shown in Figure 2.

4.1 Statistical analysis of group time interval
4.1.1 Travel rules of ride-hailing passengers. The calculation method of travel frequency of online ride-hailing passengers is as follows: first, the travel time interval of all online ride-hailing passengers is segmented according to hours and the time interval within one hour is

treated as 1 h. Statistics of the travel frequency of passengers in each time interval. Taking the time interval as the abscissa and the passenger travel frequency as the ordinate, the frequency double logarithm coordinate diagram of the time interval of four types of passengers is drawn, as shown in Figure 3.

Figure 3 above shows the travel interval distribution of ride-hailing passengers of four different companies. In addition, there is a prominent peak in the morning working hours, during which users use online ride-hailing more frequently.

4.1.2 Travel rules of shared bike users. The calculation method of travel frequency of shared bike users is as follows: first, the travel time interval of all shared bike users is divided into hours and the time interval within 1 h is treated as 1 h. Statistics of the travel frequency of users in each time interval. Take the time interval as the Abscissa and the user travel frequency as the ordinate, draw the frequency double logarithm coordinate diagram of the time interval of two different groups of shared bicycle users, as shown in Figure 4.

The above picture is the time interval distribution map of the two types of shared bikes of type1, type2. From the chart, we can see that the travel rules of the two types of shared bike users are relatively similar. We can see that the image shows a bimodal distribution from the picture. From the picture, we can see that the first peak is about going to work and school, while the second peak is the time of off work and school, both of which are the peak periods of traffic. Shared bikes are used more frequently. This paper also makes a further classification of shared bike users and analyzes their user activity, as shown in Figure 5 below.

Figure 5 above divides the users who share bikes into four groups, reflecting the active distribution of users sharing bikes. Group 1 and group 2 are users of shared bike type1, group 1 is users who use shared bikes on weekdays, group 2 is users on rest days, group 3 and group 4 are users of shared bike type2, group 3 is working days and group 4 is rest days. We also can see that the graphics of shared bikes in each group are similar, but by comparison, group 4 is more active than group 3 and group 4 uses shared bikes more frequently at the same time interval. Shared bikes are used more regularly on weekdays than on rest days.

4.2 Burst and memory of time interval

This section uses the indexes of burst and memory in human behavior dynamics (Brockmann *et al.*, 2006) to characterize the time interval distribution, which converts the frequency corresponding to the passenger time interval into a specific sequence. Thus, the statistical characteristics of passenger travel time intervals can be described by mathematical formulas.

4.2.1 Burst. Burst refers to a unique phenomenon in which human behavior occurs intensively in a short time and is silent for an extended period. Its definition is shown in Formula (1).

$$B = \frac{\sigma_t - m_t}{\sigma_t + m_t}.$$

(1)

where σ_t, m_t represents the standard deviation and average value of the behavior time interval distribution τ, respectively and the value range of B is in the field of $[-1,1]$. When $B = -1$, the standard deviation of the time interval is 0, the distribution of the corresponding time interval is a σ function, which is a regular periodic signal. When $B = 0$, it means that the standard deviation of the time interval is equal to the mean and the corresponding distribution is the Poisson distribution. When $B = 1$, it means that the time interval is 1, indicating that the standard deviation of the time interval is much greater than the average. The corresponding distribution has an undeniable fat tail phenomenon. When passengers travel intensively in a short period but do not appear for an extended period, the standard deviation of the time interval of passengers is much more significant than the corresponding average, showing a solid burst.

4.2.2 Memory. Memory can describe the correlation of time series of human behavior. The passenger travel time interval is arranged into a time interval sequence according to the line of time occurrence and the arrangement is set to have nτ time interval, then the series has $n_{\tau+1}$ travel behavior. The first $n_{\tau-1}$ time interval is taken as sequence 1 and the last $n_{\tau-1}$ time interval is taken as sequence 2. The correlation between the two-time series is defined as for Formula (2).

$$M = \frac{1}{n_\tau} \sum_{i=1}^{n_{\tau-1}} \frac{(\tau_i - m_1)(\tau_{i+1} - m_2)}{\sigma_1 \sigma_2} \tag{2}$$

where m_1, m_2 denotes the mean value of sequence S_1 and sequence S_2, σ_1 and σ_2 represent the standard deviation of sequence 1 and 2, respectively, τ_i Represents the frequency corresponding to the *i*th time interval and the value interval of M is $[-1,1]$. When M is greater than 0, there is a memory effect in human behavior; when M is less than 0, there is an anti-memory effect in human behavior; when M is equal to 0, human behavior has no memory.

Memory and burst describe the characteristics of human behavior time series from two dimensions by counting the explosion and memory of the travel time interval of each passenger group.

Figure 6 above shows the burst and memory distribution of shared bike users. The main distribution range of user travel Burst is -0.6 to 0.4, mainly concentrated in -0.2 to 0.2. Similarly, the main distribution range of user travel Memory is between -0.8 and 0.8. The travel time interval of users will not continue to increase or decrease, so most individual users have weak memory or no memory. From the above analysis, it can be concluded that the user group travel behavior is also a common human behavior characteristic of "strong matrix method and weak memory", but it is difficult to depict the travel mode of individual users.

4.3 Analysis of the correlation between urban points of interest and travel rules

POI represents the spatial and location attributes of geographical entities. Among them, the color from light to deep in the illustration in Figure 7a shows the change of POI density from sparse to dense. It can be seen from the map that the road network density of the central urban area of the city is the highest, followed by the Binhai New area, the density of the central urban area is the highest and concentrated in a relatively small range, the outward diffusion space is small and the density changes rapidly and there is little difference in the POI density of the central urban areas of each district and county. Figure 7b mainly shows the dense and sparse POI distribution in the city. As can be seen from the picture, the POI distribution in the central area of the city and the main urban area of Binhai New area is dense, while the distribution of POI in the north and south of the city is sparse. The overall distribution of POI is similar to that of the road network. Figure 7c is a road network distribution map, which is mainly a map of urban traffic structure, which is mainly composed of urban roads connected with each other and intertwined into a network, which can reflect

the degree of road concentration in various areas of the city. Figure 7d mainly shows the distribution of the city's road network and the analysis can be carried out from the dense and sparse distribution of the road network. As can be seen from the picture, the road network in

the central urban area of the city is dense, while that in the north and south is sparse. Because the road network density can be used to describe the road length and average distribution in the region, reflect the level of urban road supply and provide a reference basis for the analysis of urban traffic operation, it also provides basic data for the formulation of urban road management and control measures. Figure 7d the color from light to deep in the illustration shows the change of road network density from sparse to dense. It can be seen from the map that the road network density in the central urban area of the city is the highest, followed by the Binhai New area. There is a relatively dense road network connection between the central urban area and the Binhai New area and there is little difference in the road network density between the central urban areas of each district and county.

4.4 Construction of urban safety indicators

In this paper, community safety analysis is carried out by studying the correlation between urban points of interest and alarm data and combined with the travel rules of human groups.

The community safety index is defined as $ind_{comunity}$, which means that for each type of alarm event, multiplied by the hazard weight of the corresponding alarm event, the community safety index is obtained, as shown in the following Formula (3):

$$ind_{comunity} = \sum_{i=1}^{n} p_{call\_i} * weight_i. \tag{3}$$

In Formula (3), n represents the number of cases that call the police, p_{call_i} represents the number of reports of different types of cases and $weight_i$ Refers to the hazard weight of each alarm type—the greater the harm, the lower the weight and the lower the safety index.

Finally, the security analysis suggestions of different communities are given. First of all, the security index $ind_{comunity}$ Each community needs to be normalized. The normalization Formula is as follows (4):

$$ind\_normal_{comunity} = \frac{ind_{comunity} - ind_{min}}{ind_{max} - ind_{min}}. \tag{4}$$

Finally, the normalized safety index of each community is classified to judge the security of the community. Then carry on the correlation analysis; Tables 3 and 4 give the corresponding code of the relevant attributes in this paper, convenient for the correlation analysis results.

From the basic attributes of the community and alarm calls related to attribute Table 5, we can see the following phenomena:

(1) There is a high positive correlation between the total population (Y1) and the number of traffic cases reported (X4). The reason may be that the more the total population, the greater the probability of accidents, such as traffic accidents. Similarly, the larger the area, the greater the likelihood of accidents and the corresponding number of alarms will be more.

(2) According to the statistical analysis, the probability distribution of the number of alarm calls obeys the power-law distribution of $\alpha = 3.84127$ in the community and an extensive power index indicates that the probability decreases rapidly with the increase of the number of alarm calls. So that is to say, most of the alarm volume is concentrated in the case of a small number of alarm calls and the per capita alarm volume is stable between 2 and 4 in each community, regardless of the total population and population density—the area size, etc. Therefore, the basic attribute data of different communities can not be used as the prediction index of per capita alarm. Similarly, there is a similar conclusion for the average daily alarm, which also aligns with the power-law distribution. We can draw a similar conclusion with the per capita alarm according to Table 5.

(3) As can be seen in Table 5, there is a high correlation between the number of extortion alarms (X9) and the number of shared bicycles (Y2). The reason may be that people gather in places with a large number of shared bicycles and the area is well developed and has a large flow of people. The possibility of extortion cases is relatively high.

Alarm related attributes	Code	Alarm related attributes	Code
Total Number of Alarms	X1	Total Number of Robbery Alarms	X7
Total Number of Criminal Alarms	X2	Total Number of Homicide Alarms	X8
Total Number of Public Security Alarms	X3	Total Number of Fraud Alarms	X9
Total Number of Traffic Alarms	X4	Total Number of Extortion Alarms	X10
Total Number of Alarms by the Masses for Help	X5	Total Number of Kidnapping Alarms	X11
Total Number of Theft Alarms	X6	Total Number of Fight Alarms	X12

Table 3.
Alarm data code table

Community attribute name	Code	Community attribute name	Code
Population	Y1	Number of banks	Y11
Number of shared bicycles	Y2	Number of attractions	Y12
Area	Y3	Number of restaurants	Y13
The population density	Y4	Number of supermarkets	Y14
Area per capita	Y5	Percentage of residential land	Y15
Housing Prices	Y6	Percentage of road facilities	Y16
Number of bus stops	Y7	Percentage of Greenland Plaza	Y17
Number of hospitals	Y8	Percentage of hospital land	Y18
Number of schools	Y9	Distance from city center	Y19
Number of police stations	Y10		

Table 4.
Community attribute code table

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Y1	0.130	0.053	0.118	0.492	0.134	0.049	0.016	0.094	0.081	0.054	-0.109	0.105
Y2	0.112	0.092	0.100	0.191	0.118	0.073	0.194	0.087	0.187	0.063	0.044	0.087
Y3	-0.061	-0.071	-0.058	-0.001	-0.061	-0.052	-0.189	0.014	-0.167	-0.106	-0.086	-0.062
Y4	-0.041	0.011	-0.048	-0.177	-0.041	0.005	0.072	-0.032	0.041	-0.033	0.051	-0.055
Y5	-0.005	0.020	-0.010	-0.241	0.008	0.032	-0.063	-0.202	-0.024	-0.020	-0.078	-0.010
Y6	0.268	0.255	0.252	0.402	0.263	0.244	0.232	0.159	0.320	0.190	0.091	0.250
Y7	0.276	0.218	0.274	0.611	0.258	0.209	0.114	0.062	0.281	0.088	-0.050	0.259
Y8	0.057	0.060	0.067	0.160	0.035	0.055	0.048	-0.050	0.101	0.092	-0.099	0.071
Y9	0.530	0.488	0.540	0.444	0.508	0.473	0.373	0.320	0.549	0.220	0.318	0.525
Y10	0.064	0.019	0.041	0.266	0.083	0.008	-0.161	-0.158	0.191	-0.143	0.041	0.008
Y11	0.056	0.007	0.053	-0.032	0.079	-0.003	-0.051	-0.151	0.112	0.047	0.140	0.047
Y12	0.206	0.128	0.195	0.427	0.215	0.118	-0.036	-0.142	0.273	0.012	-0.021	0.160
Y13	0.229	0.150	0.223	0.540	0.225	0.135	0.072	-0.024	0.265	0.154	-0.081	0.187
Y14	0.131	0.157	0.134	0.093	0.113	0.165	0.130	0.192	0.058	0.057	0.036	0.139
Y15	-0.115	-0.132	-0.113	-0.065	-0.107	-0.138	-0.054	0.079	-0.099	0.070	0.080	-0.102
Y16	0.107	0.119	0.100	0.014	0.110	0.114	0.079	0.019	0.115	-0.041	0.015	0.080
Y17	-0.216	-0.202	-0.202	0.048	-0.240	-0.200	-0.262	-0.219	-0.149	-0.143	-0.185	-0.204
Y18	-0.014	0.061	-0.039	0.012	-0.016	0.064	0.171	0.096	0.024	0.026	-0.017	-0.038
Y19	0.162	0.094	0.171	0.178	0.166	0.079	0.050	-0.076	0.214	0.045	0.023	0.158

Table 5.
Basic attributes of the
community and
properties related to
alarm calls

(4) It can be seen that there is a certain positive correlation between the number of hospitals, the number of bus stops and the total number of 110 alarms (X1). The reason may be that the more hospitals and bus stations there are, the higher the population density is and the type of alarm often causes the type of alarm. There is a strong correlation between the number of police stations (Y9) and the total number of 110 alarms. The reason for this situation can be considered on the basis of practical experience. According to the accumulated experience over the years, the relevant 110 police situation handling personnel will place a relatively large number of police stations in areas with many alarms. However, the correlation between the number of police stations and the number of police stations in Table 5 can be demonstrated by the correlation value of 0.530. The number of police stations here is also an important independent variable index for estimating alarm volume.

(5) It can be found that there is a significant correlation between criminal cases (X2) and the number of police stations (Y10). This may indicate that many factors will be integrated with the process of selecting the location of the police station. The choice of the address of the police station will undoubtedly be arranged according to the number of criminal cases in history. It can also be seen that there is a significant correlation between the number of police stations and almost all cases, which further shows that the location of police stations will comprehensively consider the occurrence of various types of historical alarm cases.

(6) It can also be found in Table 5 that there is a significant positive correlation between the number of traffic cases (X4) and the number of hospitals (Y8), bus stations (Y7), banks (Y11), restaurants (Y13) and supermarkets (Y14). It can be considered that there is more traffic in hospitals, bus stations, banks, restaurants and supermarkets and the possibility of traffic accidents is relatively greater.

(7) There is no correlation between the number of cases (X8) and all community attributes except the number of police stations (Y9). The reason is that the number of cases is rare and what happens is random from a macro point of view, so all community attributes except the number of police stations have nothing to do with it.

Next, the human alarm time characteristics are described by the alarm interval time burst coefficient and memory coefficient of each street. It can be seen in Figure 8 that the mean point is Bamboo 0.08607 and memory 0.009544 and the paroxysmal memory is close to zero. It is found that the alarm behavior of street people has the characteristic of weak memory.

The reason for calculating the community safety index through the number of different police cases is that according to the correlation analysis, this paper evaluates the community safety index results of 60 community streets. It calculates each community safety index according to formula (3). Table 6 is obtained according to formula (4) normalization.

As can be seen from Table 6, it is found that about 60% of the community streets are in average safety condition. In contrast, only a tiny number of community streets are in good condition and the relevant street security personnel need to take further safety measures to ensure community safety.

5. Conclusions

According to characteristics of urban spatial structure, it is found that there is a close relationship between people's behavior patterns and urban public safety indicators. And through the analysis of the behavior model, the experimental results can provide a reference for urban public safety indicators. Group behavior modeling and analysis technology are widely used in various fields, especially in social security. Based on the sensor data of shared

bikes and ride-hailing in a large city in China, this paper makes an in-depth study on the internal structure period and volatility of group behavior, time intervals (such as the relationship between individuals) and urban points of interest and travel rules through the observation and analysis of traffic behavior dynamics under various traffic patterns, such as urban spatial structure and human traffic behavior patterns. It is found that there is a difference in power index when users choose additional ride-hailing services. There is a positive correlation between the shared bike user activity and the power law bimodal phenomenon in the double logarithmic coordinate system. Finally, we analyzed the city.

For the future work in this paper, Although this paper analyzes the dynamic behavior of multiple traffic in two shared datasets and obtains more meaningful dynamic results, some problems still have to be solved. For example, we only analyzed two shared vehicles. Our focus will be to study multi-level traffic behavior based on more shared sub-tools to serve the city's public safety better.

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Further reading

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