Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-023-02577-y OPEN

Daily rhythm of urban space usage: insights from the nexus of urban functions and human mobility

Fangye Du [1], Jiaoe Wang [2,3✉], Liang Mao [4] & Jian Kang [1]

As urban density increases, it becomes increasingly common for multiple functions to coexist within the same space, intensifying the complexity of human activity dynamics. However, traditional urban zoning, which relies on the spatial distribution of urban functions and human activities, focuses on the spatial heterogeneity of urban space and fails to capture the temporal dynamics of urban space usage. This paper aims to investigate the daily rhythm of urban space usage and illustrate how the distribution and combination of urban functions affect the daily usage rhythm. Taking Beijing in China as a case, we first identified the daily rhythm of urban space usage with the k-means algorithm and zoned urban space accordingly. Subsequently, multinomial logistic (MNL) models were employed to elucidate how the distribution and combination of urban functions influenced these daily usage patterns. Furthermore, a validation study in typical zones was conducted. The results revealed the existence of a distinct daily rhythm in urban space usage, resulting in the classification of urban space into seven distinct zones: high equilibrium, low equilibrium, diurnal, nocturnal, morning, evening, and noon-type zones. Also, we found that this daily usage rhythm is closely intertwined with the distribution and coexistence of urban functions. Our findings could provide valuable insights for the enhancement of various intricate aspects within urban decision-making processes, including urban planning, transportation management, and more, at a fine-grained scale.

[1] School of Public Affairs and Administration, University of Electronic Science and Technology of China, Chengdu 611731, China. [2] Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A, Datun Road, Chaoyang District, Beijing 100101, China. [3] College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China. [4] Department of Geography, University of Florida, Gainesville, FL 32611, USA. ✉email: wangje@igsnrr.ac.cn

Introduction

Urban space is often partitioned into distinct urban zones characterized by shared attributes such as urban functions. This division assumes a pivotal role in promoting efficient resource utilization and facilitating sustainable urban development. As urban density rises, the diversity of urban functions and the dynamics of human mobility (usage) within specific zones have intensified (Zinman and Lerner, 2020). For instance, conventional shopping malls have evolved into integrated complexes that combine shopping, commercial, entertainment, catering, and more. Consequently, a certain zone might function as a workplace during the day, transition into a catering venue at noon, and then evolve into an entertainment hub at night. A deeper understanding of the temporal patterns and fluctuations in urban space usage – referred to as the daily rhythm of urban space usage – provides invaluable insights into the intricacies of urban dynamics, which is crucial for fine-grained urban management and planning.

Over the years, a range of techniques and datasets have been utilized to establish urban zoning strategies firmly grounded in functional categorization (Tian et al. 2010; Gan et al. 2020). Initially, field observation or remote sensing data were utilized to classify urban land use, distinguishing features such as green spaces, water bodies, and impervious surface. In the era of big data, human-tracking data, such as mobile phone data, GPS data, smart-card data, and social media data, furnish valuable insights into how urban space is utilized. Therefore, numerous researchers have embarked on the integration of these human-tracking data with land-use data, delineating distinct residential, commercial, and open zones based on the spatio-temporal characteristics of each activity using a cluster method (Ratti et al. 2006; Calabrese et al. 2013; Frías-Martnez and Frías-Martnez, 2014). For instance, Pei et al. (2014) classified urban areas into residential, business, commercial, open space, and other categories with mobile phone data using a semi-supervised fuzzy c-means clustering method. Gan et al. (2020) categorized metro stations into seven clusters, including employment-oriented stations, residential-oriented stations, spatial mismatched stations, and others, based on distinct ridership patterns using a clustering method.

Traditional theories, such as the Central Place Theory initiated by Christaller, the Neo-Classical Model, and the New Economic Geography represented by Krugman, along with Urban Ecology, illuminate the mechanisms of urban functions distribution from various perspectives (Haghani et al. 2023). As human mobility intricately interacts with urban functions, these theories provide valuable insights for understanding the mechanism of human mobility in urban space (Liu et al. 2012; Calabrese et al. 2013; Balsa-Barreiro et al. 2021). As urban density increases, it's increasingly common for multiple functions coexist within the same space and thus the utilization of urban space is not solely determined by the specific function itself. This phenomenon intricately interweaves the spatio-temporal dynamics of human activity. However, traditional urban zoning, which relies on the spatial distribution of land use and human activities, has primarily focused on spatial heterogeneity of urban space and has failed to capture the temporal dynamics of urban space usage. The reason might be attributed to the oversight of the increasing complexity of urban functions, where the utilization of different urban functions is significantly influenced by the coexistence of other functions. Overlooking these nuances could result in misidentifying travel demands within urban spaces, subsequently leading to less effective interventions in the realms of smart city management and urban planning.

To fill the gaps, this paper attempted to investigate the daily rhythm of urban space usage and illustrate how the distribution and combination of urban functions effect the daily usage rhythm. First, we identified the daily rhythm of urban space usage is identified with k-means algorithm. Urban zones could be discerned based on their daily usage rhythm. Subsequently, multinomial logistic (MNL) models were employed to elucidate how the distribution and combination of urban functions influence these daily usage patterns. Finally, a validation was conducted in typical zones to illustrate the effectiveness of the aforementioned results. The insights gained from our study have significant potential to enhance various urban decision-making processes at a fine-grained scale, including urban governance, land-use planning, and transportation management.

Literature review

Methods of urban zoning. Urban zoning is the process of categorizing urban space into distinct zones, with its primary aim being to ensure the efficient utilization of urban space (Van de Voorde et al. 2011; Pei et al. 2014; Tian et al. 2010; Gao et al. 2017). Current urban zoning primarily relies on the spatial distribution of land use and urban functions. Initially, field observations were commonly used to map land use in cities, serving as the foundation for delineating urban zones. However, this approach is highly costly and time-consuming. Subsequently, remote sensing techniques and satellite images emerged as an alternative, given it can quickly obtain land cover information and classify it into categories, such as water bodies, green spaces, and impervious surface. Both field observation and remote sensing techniques are ground in land use, and they don't consider specific functions (Liu et al. 2022).

In the era of big data, researchers have increasingly resorted on human mobility data, point-of-interest (POI) data extracted from electronic maps, and location information collected from social media platforms, to identify urban functional zones (Xu et al. 2021; Zhang et al. 2022). For example, Pei et al. (2014) classified urban zones into residential, business, commercial, open space, and other categories using mobile phone data and a semi-supervised fuzzy c-means clustering method by identifying the similarity of calling patterns within each land-use type. Wu et al. (2022) mapped urban functional zones by integrating building shapes, POI attributes, cellphone user locations, and textures from remote sensing images. These studies zoning the urban space primarily focuses on capturing the spatial heterogeneity of land use and urban functions. However, a certain urban zone is often located multiple functions, with these functions serving different human activities at various times of the day (Gao et al. 2017; Tu et al. 2017). As of now, the temporal heterogeneity of urban space has received limited consideration in urban zoning practices.

Spatio-temporal dynamics of human mobility with big data. In the age of big data, a wealth of human-tracking information can be extracted from various sources, including GPS devices (Xu et al. 2016; Wang et al. 2023), social media (Longley et al. 2015; Long et al. 2018), transportation records (Huang et al. 2018), and mobile phone data (Gonzalez et al. 2008; Louail et al. 2015; Woods et al. 2022). These diverse datasets provide valuable insights into exploring the spatio-temporal dynamics of human mobility, both between cities and within cities, on an hourly, daily, monthly, and annual basis (Wei et al. 2021; Wang et al. 2023). Notably, among these diverse datasets, mobile signaling data stands out, boasting high penetration rates and extensive sample coverage. This specificity renders it particularly valuable for research in the realms of human behavior and urban studies. A subset of studies has predominantly focused on analyzing the patterns or laws of human mobility within a day in an urban context (Ratti et al. 2006). For example, Widhalm et al. (2015) revealed activity patterns that emerge from cellphone data by analyzing relational signatures of activity time, duration, and land use. Wang et al. (2023) explored the spatio-temporal variation of taxi usage in Beijing at a 1×1 km grid cell scale and its interactions with alternative transport modes, socioeconomic factors, and built environments.

As the patterns of human mobility are closely tied to the specific functions in these zones, some studies paid great attention to the spatio-temporal dynamics of a certain activities, such as commuting, recreation, education, health-seeking, and et al., using human-tracking data (Diao et al. 2016; Huang et al. 2018; Wang et al. 2020; Wang et al. 2022a). For example, Tu et al. (2017) investigated hourly urban function usage based on commuting activities inferred from mobile phone positioning data and other activities inferred from social media data. Du et al. (2020) extracted health-seeking behavior from transit smart-card data under a set of spatial, temporal, and behavioral constraints. Widhalm et al. (2015) developed a probability-based approach to extract daily activities, such as in-home activities, work-related activities, shopping, and leisure, from mobile phone data. Urban space usage pertains to the manner in which individuals utilize urban space, with a specific emphasis on the intricate interplay between human mobilities and urban space. Consequently, when viewed through the lens of urban space, human mobility over time and space reflects the spatio-temporal dynamics of urban space usage. Despite these efforts, there has been a notable lack of focus on comprehensively summarizing the various daily usage rhythms of urban space, which is a critical element in improving urban management efficiency and resource allocation.

Factors associated with human mobility. At a micro scale, such as within urban space, human mobility intricately intertwines with various urban functions, including industrial, service, commercial, and residential areas (Liu et al. 2012; Calabrese et al. 2013; Bedini and Bronzini, 2016). Over time, numerous studies have delved into understanding the determinants and mechanisms shaping the spatial distribution of urban functions, providing valuable insights into comprehending human mobility (Haghani et al. 2023). For instance, Central Place Theory, introduced by geographers Christaller, elucidates the distribution of commercial services and facilities within cities and towns (Christaller and Baskin, 1966). The New Classical Location Theory, as articulated by Alonso, underscores the influence of market forces and the significance of the city center. It also highlights the impact of factors such as transportation networks and land prices on the distribution of commercial and residential zones (Alonso, 1964). New Economic Geography, proposed by Krugman et al. (Krugman, 1996; Martin and Sunley, 1996), underscores the influence of economic scale and transportation costs on the development and functional layout of cities. Furthermore, Urban Ecology regards the spatial dynamics of urban functions as a form of ecological competition and summarizes the evolution patterns of urban residential space as the concentric circle model, sectoral model, and multi-core model (Hoyt, 1939).

In the second half of the twentieth century, time geographers began to use a “space-time aquarium” describing the trajectories of human mobility (Torsten, 1970). This approach clarifies the potential interplay between human mobility and urban functions on a micro-spatial and temporal scale. The rapid growth of Information and Communication Technology (ICT) has enabled the acquisition of extensive data related to human behavior, such as mobile phone call records and social media location data. This has led to a diverse range of research topics, investigating the trajectories of different populations within micro time windows and examining the factors influencing human mobility (Gonzalez et al. 2008; Wang et al. 2023). For instance, Liu et al. (2012) classified Shanghai, China, into six traffic ‘source-sink’ areas using taxi trajectory data, unveiling a close association with commercial, industrial, residential, institutional, and recreational zones. Wang et al. (2022b) demonstrated that areas with high bus ridership are primarily situated near the central business district (CBD), transport hubs, and residential areas. Primarily, noteworthy studies suggest that human mobility is intricately concentrated in certain urban functions. However, they often neglect the dynamic interplay between human mobility and urban functions at a micro-temporal level, such as hour by hour within a day, referred to the daily rhythm of urban space usage.

Conceptual framework

Traditional urban zoning, which relies on the spatial distribution of land use and urban functions, focused on spatial heterogeneity of urban space and failed to capture the temporal dynamics of urban space usage. In the era of big data, human-tracking data furnish valuable insights into how urban space is utilized. Related studies have investigated the spatio-temporal distributions of urban space usage and corresponding human activity patterns for specific urban functions. Grounded in existing studies and new context of urban development, some distinct issues warrant attention. First, as urban density increases, it becomes more common for multiple functions to coexist within the same space, increasing the complexity of human activity dynamics. For example, a specific zone might serve as a workplace during the day, transition into a catering venue at noon, and then evolve into an entertainment hub at night. Therefore, it is essential to identify urban zones based on the daily rhythm of urban space usage, also known as the temporal patterns of urban space utilization. Furthermore, an individual’s engagement with a specific urban function is intricately linked not only to the function itself, but also to the presence of coexisting functions. Put differently, the influence of coexisting urban functions on urban space usage is mutually influential. This study attempts to address the aforementioned issues (Fig. 1). To achieve this, we first discerned the daily

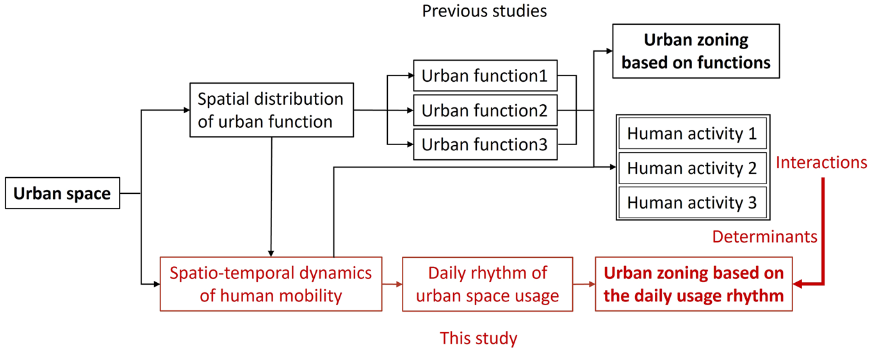

Fig. 1 Conceptual framework.

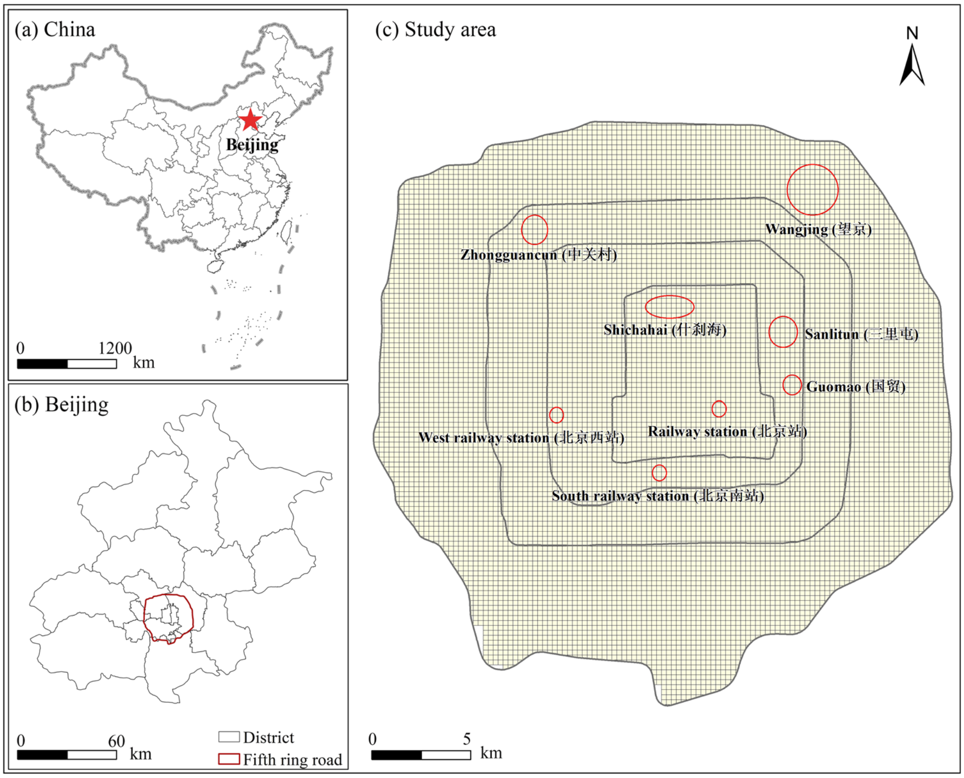

Fig. 2 Introduction on study area. a Location of Beijing in China, **b** location of the study area in Beijing, **c** study area (areas within the fifth ring road of Beijing) and unit (250 × 250 m grid cell).

rhythm of urban space usage using mobile singling data and k-means algorithm. This allowed us to partition urban space into distinct zones predicated on their daily usage rhythm. Subsequently, how urban functions and their interactions shaped the daily usage rhythm of urban space was investigated.

Methodology

Data collection and processing. We select areas within the fifth ring road of Beijing, China, as our study region (Fig. 2), where both land use and human mobility are highly urbanized and diverse. To investigate urban function usage at a fine spatial scale, we divide the study region into 10,889 grid cells at a resolution of 250 × 250 m.

Points of interest (POI) data for urban function. Urban functions in grid cells are determined by the point-of interest (POI) data. We collected information on the name, latitude, longitude, and facility category of approximately 180,000 POIs in our study region from Baidu map (https://lbsyun.baidu.com/) in August 2017. The POI categories include enterprises, entertainment venues, residences, schools, living facilities, hospitals, government buildings, shops, restaurants, gyms, and tourism-related establishments. Each type of POI corresponds to a specific city function. Table 1 shows the corresponding relationship between POI and urban function, as well as the statistics of POIs by category and by grid cell.

Table 1 Urban functions and statistics of POIs by category and by grid cell.

POI category	Urban function	Maximum	Average	S.D.
Enterprise	Working	100	6.9	14.4
Entertainment facilities	Recreation	32	0.3	1.1
Residence	Residing	49	1.6	2.4
School	Education	2	0.6	2.1
Hospital	Seeking healthcare	3	0.2	0.8
Government	Working	41	0.7	1.9
Shop	Shopping	9	0.3	0.7
Restaurant	Catering	113	3.3	6.8
Park	Touring	25	0.4	1.4
Tourism	Touring	1	0.3	1.1

Mobile signaling data (MSD). MSD is considered a reliable proxy for studying human mobility due to the ubiquitous presence of mobile phones. In this study, we obtained MSD from China Unicom, one of the largest telecommunication corporations in China, for a period of five weekdays from January 9th to January 13th, 2017. The original MSD records consist of unique user IDs, timestamps, and locations, based on which trips of each mobile phone user during the five-day period were reconstructed. To ensure privacy protection, we aggregated the mobile phone users' locations to grid cells, resulting in about 6.8 million trips between grid cells. To focus on meaningful human activities, we filtered out trips that took less than 30 min. This threshold ensured that mobile phone users had sufficient time to engage in actual activities, such as eating out and shopping, at locations. From the mobile phone users' trip data, we derived the total number of trips originating from and arriving at each grid cell in the five-day study period. Additionally, we calculated the average number of destinations in each grid cell for every hour, resulting in a time-space matrix with a dimension of 24 × 10,889, where the 24 rows refer to the 24 h in a day and the 10,889 columns are the number of grid cells. Figure 3 shows the spatial and temporal patterns of destination extracted from the MSD.

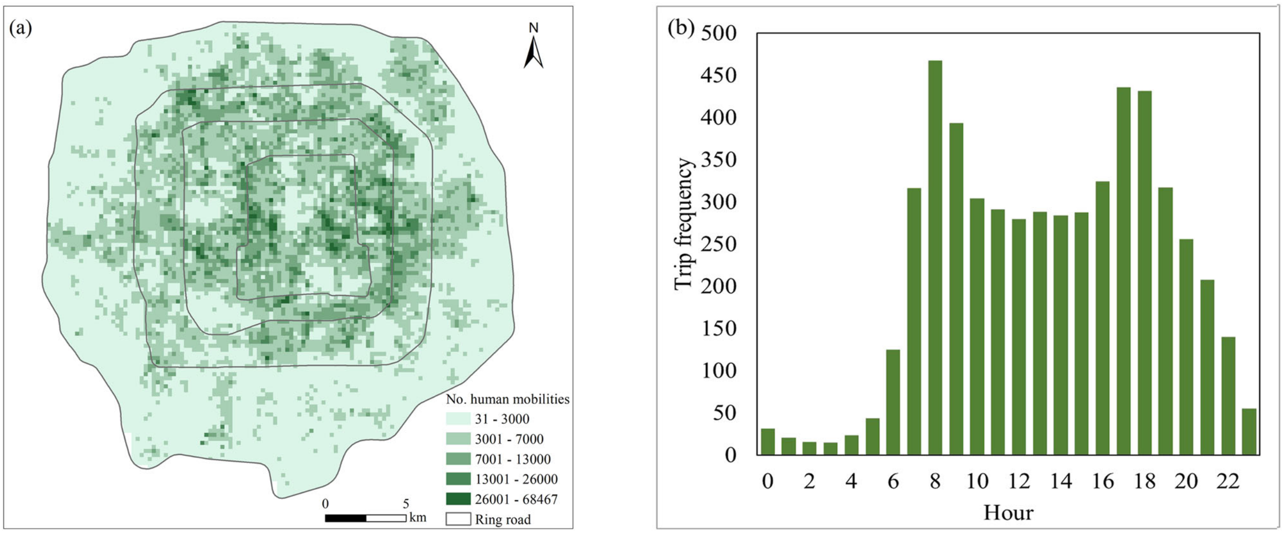

Fig. 3 Spatio-temporal patterns of human mobility destinations. **a** Spatial pattern and **b** temporal pattern.

K-means algorithm. K-means algorithm is a widely used unsupervised classification method that aims to maximize the differences between groups and minimize the differences within each group. The algorithm follows these steps. First, K cluster centers are randomly generated in the dataset. Second, all the samples are assigned to the K cluster based on the difference between each sample and the K cluster center, which is the preliminary clustering result. Third, the centroid of each cluster, the mean of the samples in each cluster, is calculated as the new cluster center. Repeat step two and three, until the cluster center does not change.

The K-means algorithm in IBM SPSS Statistics 26.0 was applied to characterize the daily usage patterns of urban spaces. Noteworthy fluctuations in travel volume across different time intervals were evident in Fig. 3. To mitigate potential variations in travel volume among units affecting clustering outcomes, data normalization was conducted using a standard deviation multiplier. Following this, the "Hierarchical Cluster Analysis" function was employed to create a Tree Diagram, facilitating the visualization of daily urban space usage patterns and identifying seven distinct cluster numbers. Ultimately, the "k-means clustering" function in IBM SPSS Statistics 26.0 was utilized to delineate seven distinct types of daily rhythms in urban space usage.

Multinomial logistic (MNL) model. To explore how urban functions or their combinations influence the daily rhythm of urban space usage, MNL models were employed with the software of Stata 16.0. MNL model is constructed based on the principles of random utility theory and consists of a collection of logit models, each representing a distinct discrete choice. Specifically, the utilization of urban space n falls within daily rhythm type i, denoted as U_{ni}, is formulated as:

$$\mathrm{U}_{ni} = \beta_{i0} + \beta_{i1}x_{ni}^{1} + \cdots\cdots \beta_{ik}x_{ni}^{k} + \cdots\cdots + \beta_{im}x_{ni}^{m} + \varepsilon_{ni} \quad (1)$$

where x_{ni}^{k} is the kth ($k = 1, 2, 3\ldots, m$) explanatory variable, and β_k is the estimated coefficient for this variable. ε_{ni} is a random error item that obeys the Gumbel distribution. If utility-maximizing behavior is assumed, the probability of utilization of urban space n having daily usage rhythm i, denotes as P_{ni}, is formulated as Eq. 2:

$$\mathrm{P}_{\mathrm{ni}} = e^{u_{ni}} / \textstyle\sum_{j\in c} e^{u_{nj}} \quad (2)$$

where C is the set of daily rhythm of urban space usage. Coefficients β_{ik} in Eq. 1 can be estimated for each daily rhythm i, based on the logistic regression method. The 'mlogit' command in Stata 16.0 is utilized to execute the Multinomial Logit (MNL) model. The significance of our models is evaluated using the chi-square test's p-value. If the p-value is below the chosen significance level ($p \le 0.01$, $p \le 0.05$, or $p \le 0.1$), the model is considered statistically significant. Subsequently, the 'fitstat' command is employed to acquire indicators assessing the goodness of fit, including the log likelihood, AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and McFadden's R^2. Lower values for log likelihood, AIC, and BIC indicate a superior model fit, whereas a higher McFadden's R^2 value suggests a better fit.

Results and discussion

Urban zoning based on the daily rhythm of urban space usage. The K-means algorithm was utilized to classify each grid cell within the urban space based on human usage (human mobility) during different time intervals, effectively capturing the daily rhythm of urban space usage. The outcomes of the K-means clustering yield seven types (refer to Fig. 4): high equilibrium, low equilibrium, nocturnal, morning, evening, noon, and diurnal. Among these, the two equilibrium types exhibit a relatively uniform distribution of human usage (human mobility), with the low equilibrium type indicating lower usage and the high equilibrium type indicating higher usage levels. The nocturnal-type is characterized by sustained and concentrated human mobilities from 4:00 pm to 5:00 am of the subsequent day, while the diurnal-type exhibits a similar pattern of human mobilities but from 5:00 am to 2:00 pm. Additionally, there are three distinct peak zone types where human mobilities experience abrupt surges during specific hours of the day. The morning-type, noon-type, and evening-type accommodate a significant number of people from 7:00 am to 9:00 am, 10:00 am to 2:00 pm, and 4:00 pm to 9:00 pm, respectively.

In accordance with the daily rhythm of urban space usage, seven distinct urban zones have been identified, as illustrated in Fig. 5. Overall, high equilibrium-type zone, diurnal-type zone, morning-type zone, and noon-type zone primarily concentrated in the core urban areas, whereas evening-type and low equilibrium-type zones predominantly situate on the periphery of the city. More specifically, high equilibrium-type zones mainly concentrate in important business areas such as *Sanlitun*, *Chaoyangmen*, and *Guomao*, and the train stations. The diurnal-type zones are widely distributed in the city center and job clusters such as *Zhongguancun* and *Wangjing*. The evening-type zones is closely related to the entertainment activities and the

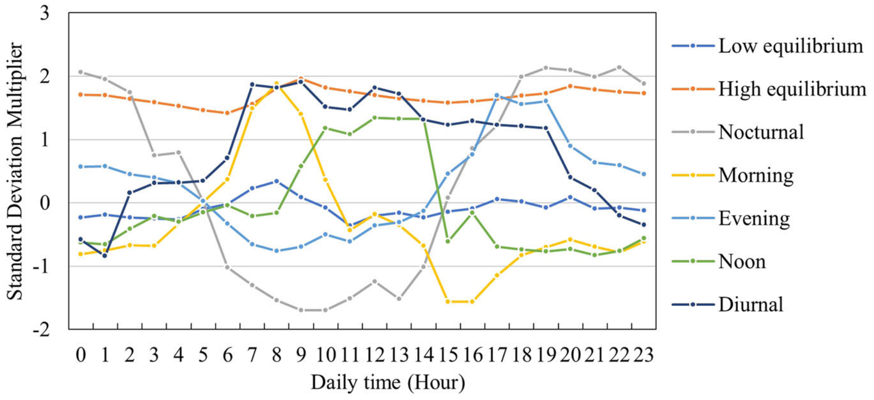

Fig. 4 Daily rhythm of urban space usage.

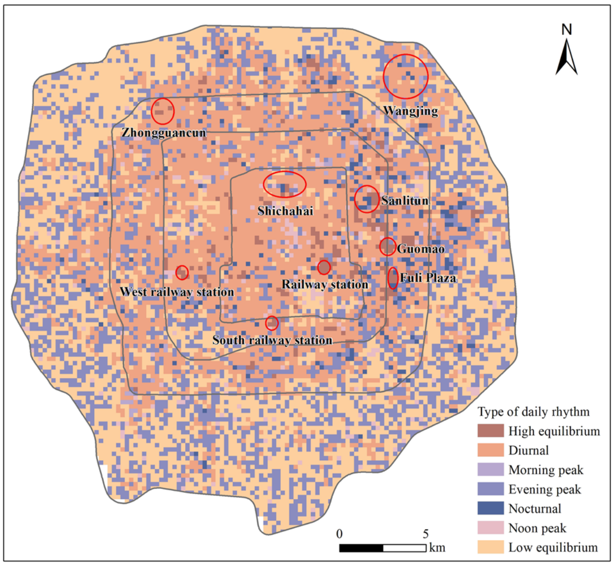

Fig. 5 Spatial distribution of urban space with diverse daily usage rhythms.

counterpart areas are located in bar street and entertainment venues, such as *Shichahai* and *Sanlitun*. In addition, the low equilibrium-type zones are widely distributed on the periphery of the city and interspersed within other types of urban zones.

Urban functions associated with the daily usage rhythm

Model specification. To comprehensively investigate the impact of urban functions and their interactions on the daily rhythm of urban space usage, MNL models were employed. For model specific, seven temporal patterns of urban space usage, identified in section 5.1 served as dependent variable of all models, denoted as C in Eq. 2. Among these temporal patterns, low equilibrium type is set as the reference category. Meanwhile, the independent variables consist of the number of facilities related to working, residing, catering, seeking healthcare, living, recreation, education, shopping, leisure, touring, and their interactions. To account for the influences from co-occurring functions, interaction terms between any two urban functions are also incorporated in the model. Furthermore, the distance to city center is used as the control variable.

Prior to modeling, diagnostic statistics of the MNL model was conducted. Firstly, the presence of multicollinearity was examined by calculating the Variance Inflation Factor (VIF) values between the independent variables. It was observed that strong multicollinearity exists between the interaction terms and the independent variables. Additionally, the initial model failed to fit the data. To tackle this challenge, a solution was put forth that involves categorizing the independent variables into 9 groups. The first group is the number of POIs associated with diverse functions such as working, residing, catering, seeking healthcare, recreation, education, shopping, leisure, and touring. The remaining groups encapsulate interactions between a specific function and the entirety of other functions, presented in the form of their product (refer to Table 2). For instance, the second group delves into the interdependencies between work and the array of other functions. This approach enables the independent variables and interaction terms to be effectively incorporated without multicollinearity concerns. Subsequently, it is argued that the endogeneity problems have negligible effects on the model results. Two potential causes of endogeneity in this study are reverse causation and missing variables. Concerning reverse causality, the facilities are tangible entities existing in physical space, and their presence is unlikely to be influenced by human mobility. Therefore, it is believed that reverse causality is unlikely to be a major factor contributing to endogeneity in this context. To mitigate the potential endogeneity resulting from missing variables, the model includes as many influencing variables as possible to capture the effects of urban functions distribution on the daily usage rhythm.

Table 2 Variables of models.

Model	Urban functions as independent variables
Model 1	No. Working (W), No. Residing (R), No. Catering (C), No. Seeking healthcare (H), No. Entertainment (E), No. Education (D), No. Shopping (S), No. Touring (T)
Model 2	W × R, W × C, W × H, W × E, W × D, W × S, W × T
Model 3	R × W, R × C, R × H, R × E, R × D, R × S, R × T
Model 4	C × W, C × R, C × H, C × E, C × D, C × S, C × T
Model 5	H × W, H × R, H × C, H × E, H × D, H × S, H × T
Model 6	E × W, E × R, E × C, E × H, E × D, E × S, E × T
Model 7	D × W, D × R, D × C, D × H, D × E, D × S, D × T
Model 8	S × W, S × R, S × C, S × H, S × E, S × D, S × T
Model 9	T × W, T × R, T × C, T × H, T × E, T × D, T × S

No. means the number of. For example, working means the number of working facilities within each zone.

Model interpretation. The *p*-value of chi-square test showed that all models were statistically significant at the 0.01 level, implying the meaningful contribution of the independent variables in explaining the dependent variable. Moreover, the calculated values of log likelihood, AIC, BIC, and McFadden's R^2 for all models indicated a good goodness of fit. These findings affirmed the reliability and effectiveness of our models in explaining the daily rhythm of urban space usage.

Table 3 Result of MNL models.

Urban function	High equilibrium	Diurnal	Nocturnal	Morning	Evening	Noon
Functions						
W	13.86***	9.08***	11.12	3.71***	5.72	0.74
R	12.31***	4.05***	43.72***	−9.25	6.72***	6.27
C	10.85***	3.06***	19.67	6.01***	7.52***	5.06***
H	14.78***	16.29***	43.87***	13.81***	1.68	7.73***
E	6.84***	6.03	13.63***	6.78	4.48***	5.37
D	3.57***	4.91***	12.30	9.33***	2.33	15.05
S	10.21***	4.74***	21.73	3.23	4.32***	7.42
T	6.93***	2.11***	42.33	14.78***	1.58***	20.95***
Interactions						
W × R	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$
W × C	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+$	$+$
W × H	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$
W × E	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$
W × D	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+$	$+$
W × S	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+$
W × T	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$
R × C	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$	
R × H	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
R × E	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+$
R × D	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$
R × S	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+$
R × T	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
C × H	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$
C × E	$+^{***}$	$+$	$+^{***}$	$+$	$+^{***}$	$+$
C × D	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+$
C × S	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$
C × T	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$
H × E	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
H × D	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$
H × S	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
H × T	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
E × D	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+$
E × S	$+^{***}$	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+$
E × T	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$
D × S	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+$
D × T	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$
S × T	$+^{***}$	$+^{***}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$

The multiple models resulted in the same interaction term being present in several different models. Thus, the interaction terms only demonstrate the significance and direction of the coefficient.
$^{***}p < 0.01$.

The result of MNL models is shown in Table 3. It revealed significant statistical relationships between urban functions and the daily rhythm of urban space usage. The presence of working function in zones are more likely to pertain to high equilibrium, diurnal, and morning types, when compared to low equilibrium-type zones. This phenomenon could be attributed to the utilization of working functions throughout both daytime and nighttime, particularly during the morning peak hours. Residing function in zones increases the likelihood of categorization as high equilibrium, diurnal, nocturnal, and evening types, in contrast to low equilibrium-type zones. It is because residing function exhibits a more constant usage pattern, extending from day to night, with notable peaks during the noon and evening hours. Catering function in zones contribute to the categorization of zones as high equilibrium, diurnal, morning, evening, and noon types as opposed to low equilibrium-type zones. The underlying logic for this observation can be succinctly summarized: the catering function is employed during the bustling peak hours of breakfast, lunch, and dinner. As a result, there is an increased likelihood that the areas where this function is present will be designated as morning-type, noon-type, and evening-type zones. Simultaneously, since the catering function often coexists with other activities like work, residence, and tourism, it also plays a role in categorizing zones as high equilibrium-type zones.

Seeking healthcare function promotes the temporal dynamics of human mobility within zones present high equilibrium, diurnal, nocturnal, morning, and noon types. The hospital is busy throughout the entire day, with a notable increase in activity during the morning and noon hours, which are closely associated with patient registration. The presence of entertainment function enhances the likelihood of zones being categorized as high equilibrium, diurnal, nocturnal, and evening types. This can be attributed to that entertainment functions are typically utilized during the evening, contributing to a higher probability of the zones where they exist being classified as evening-type and nocturnal-type zones. Due to their prevalence in areas with frequent activity, the regions where they are present may also fall under the category of high equilibrium-type zones. Zones with education function are more likely to be part of high equilibrium, diurnal, and morning-type zones in contrast to low equilibrium-type zones. This phenomenon can be attributed to the commuting and communication activities associated with school attendance, particularly during the morning peak hours. The shopping function enhances the temporal dynamics of human mobility within zones characterized by high equilibrium, diurnal, and evening types. Conversely, the touring function plays a role in shaping zones of high equilibrium, diurnal, morning, evening, and

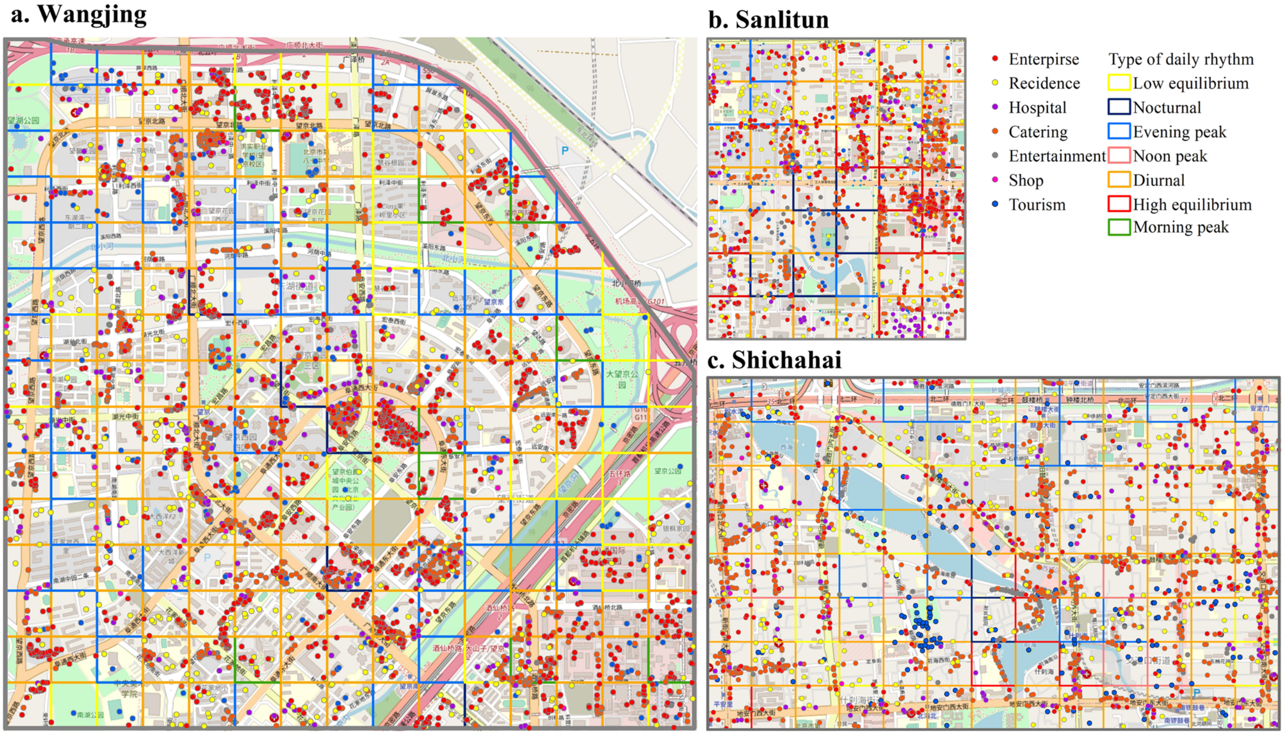

Fig. 6 Type of daily usage rhythm and distribution of urban functions in typical zones. **a** Wangjing, **b** Sanlitun, and **c** Shichahai.

noon types. All these phenomena are closely related to the temporal attributes of the specific activities.

Our findings also underscore the interactive effects of diverse urban functions on the daily rhythm of urban space usage. Comparing the significance of urban functions and their corresponding interaction terms, we observed that the effects of specific functions on the daily usage rhythm have been modified in the presence of coexisting functions, while others maintain unaltered impacts (Table 3). This phenomenon occurs as specific functions take on dominant roles when coexisting with others, whereas certain functions frequently function as accompanying elements. Specifically, working, residing, seeking healthcare, education, and touring functions consistently assume dominant roles when co-occurrence with other urban functions. When these functions exist simultaneously, the impacts of the two functions on the daily rhythm of urban space usage exhibit a cumulative effect. For instance, the presence of working functions in zones increases the likelihood of categorization as high equilibrium, diurnal, and morning types. Likewise, the presence of residing functions in zones enhances the inclination to be classified as high equilibrium, diurnal, nocturnal, and evening types. However, in zones where both working and residing functions coexist, the likelihood of being classified as high equilibrium, diurnal, and nocturnal types is amplified, contrasting with the low equilibrium type. Shopping functions act as the dominant function when coexisting with other urban functions, except for touring. When paired with touring, shopping functions serve as an accompanying function. Catering functions predominantly act as an accompanying function when coexisting with functions related to work, residing, seeking healthcare, education, and touring. However, when catering functions coexist with shopping and recreation, both functions might assume dominant roles.

Validation in typical zones. To illustrate the effectiveness of the aforementioned results, we presented the temporal dynamics of human mobility and the distribution of urban functions in three typical areas: *Wangjing* (望京,featuring enterprises, malls, and residential areas), *Sanlitun* (三里屯,including enterprises, malls, bars, and residential areas), and *Shichahai* (什刹海,known for tourism and bars) (see Fig. 6). These zones not only concentrate a large number of activities but also encompass mixed urban functions. The *Wangjing* zone is renowned for its concentration of international companies such as Baidu, Alibaba, and NetEase. There are also residing, catering, and recreation functions. The coexistence of these functions contributes to its daily rhythm of urban space usage, which exhibits diurnal, morning peak, evening peak, and nocturnal patterns. Diurnal-type zones exhibit a high concentration of enterprises, residential areas, catering establishments, and shopping facilities. Morning-type zones typically revolve around working functions, while nocturnal areas are characterized by recreation and work-related activities. At the same time, evening-type zones primarily serve as residing function, with some catering and living functions mixed in.

The *Sanlitun* zone is characterized by a concentration of various functions, including work, catering, shopping, and entertainment, with a few residential areas mixed in. The area's daily usage rhythm includes high equilibrium, diurnal, nocturnal, and evening peak types. In terms of the relationship between urban functions and daily usage rhythm, high equilibrium areas concentrate on work, dining, and recreation functions. Diurnal zones are closely associated with work and catering functions, while the presence of evening-type zone is linked to residential functions. *Shichahai* zone is renowned for its tourism and bar street, with a mixture of some businesses and residences. Overall, the primary daily rhythm of urban space usage in the *Shichahai* zone is diurnal. However, in zones with a high concentration of bars, the daily usage rhythm exhibits nocturnal and high equilibrium types. Conversely, areas with residential functions display a low equilibrium due to the relatively lower population density in these zones.

Policy implications. Insights gained from this study have the potential to enhance urban decision-making processes at a fine-grained scale, including urban governance, urban planning, and transportation management. First, the findings provide valuable information for tailoring interventions to optimize resource allocation and improve urban livability by considering the co-occurrence of urban functions. The identification of dominant and accompanying functions when two functions coexist highlights the importance of integration and coordination among different urban functions. Urban planners and policymakers should carefully consider the interplay between functions to create synergies and enhance the efficiency of urban spaces. For instance, the design of mixed-use developments that combine working, residing, and commercial activities can promote walkability, reduce commuting distances, and foster vibrant and sustainable neighborhoods.

Secondly, the temporal variations in urban space usage emphasize the need for time-sensitive planning and provision of infrastructure and services. For example, zones with working functions, which are primarily active during the day and morning peak hours, can benefit from enhanced transportation infrastructure and services during these periods. Similarly, zones with residing functions, active throughout the day and night, may require provisions for 24-h services such as security, lighting, and public transportation to ensure the well-being and convenience of residents. Urban planners and policymakers can leverage these insights to create more vibrant, sustainable, and efficient urban spaces that cater to the diverse needs and activities of residents and visitors.

Conclusions

With the rising urban density, the coexistence of multiple functions within a shared space becomes more prevalent, thereby heightening the intricacy of human activity patterns. For instance, a single zone might function as a workplace during the daytime, transform into a dining destination at lunchtime, and subsequently evolve into an entertainment hotspot in the evening. Nevertheless, the conventional approach to urban zoning, rooted in the spatial allocation of urban functions and human activities, has predominantly concentrated on the spatial diversity of urban space, neglecting to account for the temporal attributes in urban space usage. It might lead to inaccuracies in assessing travel demands within urban spaces, ultimately resulting in less effective interventions in the domains of smart city management and urban planning. This paper fills the gaps by investigating the daily rhythm of urban space usage and illustrating how the distribution and combination of urban functions effect the daily usage rhythm. First, we identified the daily rhythm of urban space usage with k-means algorithm, allowing us to discerned urban zones based on their daily usage rhythm. Subsequently, multinomial logistic (MNL) models were employed to elucidate how the distribution and combination of urban functions influence these daily usage patterns. Finally, a validation was conducted in typical zones to illustrate the effectiveness of our results.

In conclusion, we identified a distinct daily rhythm in urban space usage, resulting in the categorization of seven distinct zones: high equilibrium, low equilibrium, diurnal, nocturnal, morning, evening, and noon-type. This daily usage rhythm is closely intertwined with the distribution of urban functions. When compared to low equilibrium-type zones, all functions tend to appear in high equilibrium-type zones. With the exception of the entertainment function, all other functions are inclined to be found in diurnal-type zones. Furthermore, working and education functions are more likely to be located in morning-type zones, whereas residing and entertainment functions tend to be present in nocturnal-type and evening-type zones. Catering and touring functions are prone to exist in morning-type, evening-type, and noon-type zones. Seeking healthcare functions are more likely to be found in nocturnal-type, morning-type, and noon-type zones, while shopping functions tend to be situated in diurnal-type and evening-type zones. Furthermore, we found that the daily rhythm of urban space usage is also influenced by the coexistence of other functions. Some functions, such as work, residence, healthcare, education, and tourism, play dominant roles when they coexist with others, whereas catering functions often complement these roles. The daily rhythm of urban space usage and the distribution of urban functions in typical zones have demonstrated the effectiveness of our findings. These findings contribute to the enhancement of various intricate aspects within urban decision-making processes, such as urban planning, transportation management, and more, at a fine-grained scale.

Data availability

The code for extracting POI data is accessible at https://github.com/fanye1994/grasp-POI-in-Baidu/tree/main, and the downloaded dataset is available from the corresponding author upon reasonable request. The mobile signaling data analyzed in this study is not publicly available to maintain the agreement with the mobile phone operator that provided the data for research. Detailed information regarding the procedure for requesting access to the mobile signaling data, supporting the findings of this study, is available from the corresponding author upon reasonable request.

Received: 6 September 2023; Accepted: 21 December 2023;
Published online: 04 January 2024

References

Alonso W (1964) Location and land use. Toward a general theory of land rent. Cambridge, MA: Harvard University Press

Balsa-Barreiro J, Morales JA, Lois-Gonzalez CR (2021) Mapping population dynamics at local scales using spatial networks. Complexity https://doi.org/10.1155/2021/8632086

Bedini AM, Bronzini F (2016) The new territories of urban planning: the issue of the fringe areas and settlement filaments. Land Use Policy 57:130–138

Calabrese F, Diao M, Lorenzo DG, Junior FJ, Ratti C (2013) Understanding individual mobility patterns from urban sensing data: a mobile phone trace example. Transp Res Part C 26:301–313

Christaller W, Baskin CW (1966) Central places in southern Germany. Prentice-Hall, Englewood Cliffs, NJ

Diao M, Zhu Y, Ferreira J, Ratti C (2016) Inferring individual daily activities from mobile phone traces: a Boston example. Environ Plan B Plan Des 43(5):920–940

Du F, Mao L, Wang J, Jin H (2020) Inferring transit-based health seeking patterns from smart card data – a case study in Beijing, China. Health Place 65:102405

Frías-Martnez V, Frías-Martnez E (2014) Spectral clustering for sensing urban land use using twitter activity. Eng Appl Artif Intell 35:237–245

Gan Z, Yang M, Feng T, Timmermans H (2020) Understanding urban mobility patterns from a spatiotemporal perspective: daily ridership profiles of metro stations. Transportation 47:315–336

Gao S, Janowicz K, Couclelis H (2017) Extracting urban functional regions from points of interest and human activities on location-based social networks. Trans GIS 21:446–467

Gonzalez MC, Hidalgo CA, Barabasi AL (2008) Understanding individual human mobility patterns. Nature 453(7196):779–782

Haghani M, Sabri S, Gruyter DC (2023) The landscape and evolution of urban planning science. Cities 136:104261

Hoyt H (1939) The structure and growth of residential neighborhoods in American cities. Federal Housing Administration, Washington

Huang J, Levinson D, Wang J, Zhou J, Wang Z (2018) Tracking job and housing dynamics with smartcard data. Proc Natl Acad Sci USA 115(50):12710–12715

Krugman P (1996) Development, geography, and economic theory. Cambridge, MA: MIT Press

Liu G, Li J, Nie P (2022) Tracking the history of urban expansion in Guangzhou (China) during 1665–2017: evidence from historical maps and remote sensing images. Land Use Policy 112:105773

Liu Y, Wang F, Xiao Y, Gao S (2012) Urban land uses and traffic 'source-sink areas': evidence from GPS-enabled taxi data in Shanghai. Landsc Urban Plan 106:73–87
Long Y, Zhai W, Shen Y, Ye X (2018) Understanding uneven urban expansion with natural cities using open data. Landsc Urban Plan 177:281–293
Longley PA, Adnan M, Lansley G (2015) The geotemporal demographics of twitter usage. Environ Plan A 47(2):465–484
Louail T, Lenormand M, Picornell M, Cantú GO, Herranz R, Frias-Martinez E, Ramasco JJ, Barthelemy M (2015) Uncovering the spatial structure of mobility networks. Nat Commun 6(1):6007
Martin R, Sunley P (1996) Paul Krugman's geographical economics and its implications for regional development theory: a critical assessment. J Econ Geogr 72(3):259–292
Pei T, Sobolevsky S, Ratti C, Shaw S, Li T, Zhou C (2014) A new insight into land use classification based on aggregated mobile phone data. Int J Geogr Inf Sci 28(9):1988–2007
Ratti C, Frenchman D, Pulselli MR, Williams S et al. (2006) Mobile landscapes: using location data from cell phones for urban analysis. Environ Plan B Plan Des 33(5):727–748
Tian G, Wu J, Yang Z (2010) Spatial pattern of urban functions in the Beijing metropolitan region. Habitat Int 34:249–255
Torsten H (1970) What about people in regional science? Pap Reg Sci Assoc 24(1):6–21
Tu W, Cao J, Yue Y, Shaw S, Zhou M, Wang Z, Chang X, Xu Y, Li Q (2017) Coupling mobile phone and social media data: a new approach to understanding urban functions and diurnal patterns. Int J Geogr Inf Sci 31(12):2331–2358
Van de Voorde T, Jacquet W, Canters F (2011) Mapping form and function in urban areas: an approach based on urban metrics and continuous impervious surface data. Landsc Urban Plan 102:143–55
Wang J, Du F, Huang J, Liu Y (2020) Access to hospitals: potential vs. observed. Cities 100:102671
Wang J, Du F, Huang J, Liu Y (2023) How do taxi usage patterns vary and why? A dynamic spatiotemporal analysis in Beijing. Comput Urban Sci 3:11
Wang J, Huang J, Yang H, Levinson D (2022a) Resilience and recovery of public transport use during COVID-19. npj Urban Sustain 2:18
Wang J, Li Y, Jiao J, Jin H, Du F (2022b) Bus ridership and its determinants in Beijing: a spatial econometric perspective. Transportation 50(2):383–406
Wei Y, Wang J, Song W, Xiu C, Ma L, Pei T (2021) Spread of COVID-19 in China: analysis from a city-based epidemic and mobility model. Cities 110:103010
Widhalm P, Yang Y, Ulm M, Athavale S, Gonzalez CM (2015) Discovering urban activity patterns in cell phone data. Transportation 42:597–623
Woods D, Cunningham A, Utazil CE, Bondarenko M, Shengjie L, Rogers EG, Koper P, Ruktanonchai WC, Erbach-Schoenberg zu E, Tatem JA, Steele J, Sorichetta A (2022) Exploring methods for mapping seasonal population changes using mobile phone data. Humanit Soc Sci Commun 9:247
Wu H, Luo WT, Lin AQ (2022) SALT: a multifeature ensemble learning framework for mapping urban functional zones from VGI data and VHR images. Comput, Environ Urban Syst 100:101921
Xu Y, Shaw S, Zhao Z, Yin L, Lu F, Chen J, Fang Z, Li Q (2016) Another tale of two cities: understanding human activity space using actively tracked cellphone location data. Ann Am Assoc Geogr 106(2):489–502
Xu Y, Song YM, Cai JX, Zhu H (2021) Population mapping in China with Tencent social user and remote sensing data. Appl Geogr 130:102450
Zhang B, Zhong C, Gao Q, Shabrina Z, Tu W (2022) Delineating urban functional zones using mobile phone data: a case study of cross-boundary integration in Shenzhen-Dongguan-Huizhou area. Comput, Environ Urban Syst 98:101872
Zinman O, Lerner B (2020) Utilizing digital traces of mobile phones for understanding social dynamics in urban areas. Personal Ubiquitous Comput 24:535–549

Acknowledgements

This work is supported by National Natural Science Foundation of China (No. 42225106, 42301190, and 42121001).

Author contributions

WJ and DF conceptualized the study, collected data, and conducted analyses. DF, WJ, and ML designed, structured, and drafted the paper. DF, WJ, ML, and KJ contributed to editing the manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This study is not related to human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Correspondence and requests for materials should be addressed to Jiaoe Wang.