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A multi-activity view of intra-urban travel networks: A case study of Beijing

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A R T I C L E I N F O

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A B S T R A C T

Urban structure is a vital aspect that profoundly influences the livability and sustainability of cities. Although extensive explorations have conducted on urban structure from the perspective of human mobility, there remains a gap in understanding urban travel networks (UTNs) and spatial structures from a multi-activity perspective. In this study, we first inferred the locations and types of daily activity for over four million Beijing residents through multi-source data fusion. Subsequently, we constructed eight UTNs based on multiple travel flows and employed spatial analysis methods and complex network analytics to explore the structural similarities and disparities across these networks. The results revealed significant spatial heterogeneity, hierarchy, and dependency characteristics within all UTNs in Beijing. Notably, the spatial patterns of UTNs reflect that the current urban structure of Beijing is a hybrid pattern, characterized by the coexistence of polycentric and sector patterns. This study provides a comprehensive portrayal of Beijing's current urban spatial structure and offers valuable scientific insights into urban spatial governance and the configuration of public facilities.

1. Introduction

Human activities and travel patterns significantly impact urban socioeconomic development, the configuration of public service facilities, transportation planning, and construction. Exploring the spatiotemporal characteristics and patterns of urban travel yields valuable insights into the spatial organization and interaction of urban space, providing a scientific understanding of the complex nature of urban systems (Lobsang et al., 2021; Long & Nelson, 2013). Consequently, the intricate nature of travel behaviors and their spatial rules is a crucial topic in urban studies, drawing considerable attention from various interdisciplinary fields, including geography, urban planning, transportation, and society (Cagney et al., 2020; González et al., 2008; Xu et al., 2023). Despite its significance, acquiring valuable information about human activities and travel behaviors is challenging. Previous research on human activities used to rely on surveys and questionnaires (Axhausen et al., 2002; Schönfelder & Axhausen, 2003). These data sources could capture the sociodemographic attributes of travelers and the activities they engaged in, thus offering rich contextual information for daily travel planning, urban space optimization, public health management, and other related fields (Brockmann et al., 2006; Zenk et al., 2011). However, the collection of travel surveys is typically expensive and time-consuming, thereby limiting the scale and scope of such studies.

The recent two decades have witnessed an increasing utilization of information and communication technologies (ICTs) in people's daily lives. These technologies, including the Global Positioning System (GPS), artificial intelligence (AI), Internet of Things (IoT), smart sensors, robots, and drones, have brought about significant changes to human activities and travel patterns, with profound implications for our daily lives and the spatial organization of human activity spaces (Kwan et al., 2007; Shaw & Yu, 2009). The application of advanced ICTs has made it possible to collect massive, dynamic, and detailed individual and group mobility data, such as GPS, smart cards, mobile phones, floating vehicles, and social media data (Liu, Gong, et al., 2015). These emerging big data have laid a strong foundation for understanding residents' travel patterns and urban structures from a micro-mobility perspective. In this context, researchers have conducted extensive empirical investigations in human mobility and urban space studies, leveraging new technologies and emerging mobility data (Alessandretti et al., 2020; Schläpfer et al., 2021; Song et al., 2010). These studies encompass various aspects, such as activity spaces (Jin et al., 2021; Spielman & Singleton, 2022), travel patterns and spatial structure (Acheampong, 2020; Liu, Liu, et al., 2015), land-use and functional zones (Chen & Yeh, 2022; Mawuenyegah et al., 2022), and environmental perception and urban vitality

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(Ruszczyk et al., 2023; Wang et al., 2022). Through these endeavors, researchers have significantly advanced our scientific understanding of the intricate spatiotemporal relationship between human activities and urban environments. Consequently, it is evident that these large-scale studies on human mobility, facilitated by new data and techniques, effectively complement the findings of small-scale, survey-based studies (Xu et al., 2021).

At the meantime, due to rapid globalization and informatization, the mobility of urban elements (e.g., population, materials, and information) has dramatically increased, profoundly impacting the structure and evolution of cities (Dadashpoor & Yousefi, 2018). Within this context, the perspective of "space of flow" has become increasingly crucial in human mobility and urban studies (Batty, 2007, 2013; Taylor et al., 2010; Ye & Liu, 2019). Under the paradigm of "space of flow", as the main component of the urban complex system, human activities and travel behaviors promote interactions between different urban spaces and affect the flow of different elements, thereby contributing to the formation of a complex network with spaces as the nodes and the flow of elements as the connections (Castells, 2011; Lobsang et al., 2021; West, 2017). Therefore, understanding the urban system from the perspectives of human mobility and network is paramount in the information era. To date, scholars and practitioners have conducted numerous studies on human activities and urban travel structures, employing various types of data and generating a wealth of research findings (Liu, Huang, et al., 2021; Xu et al., 2016; Zhong et al., 2014). However, available studies still present certain limitations.

First, existing studies have primarily focused on residents' activities and behaviors related to their homes or workplaces, or specific types of non-home-work activities like recreation, shopping, and dining, along with their spatial organization (Parady et al., 2019; Shi et al., 2023; Tao et al., 2023). However, there is a lack of comprehensive explorations into the spatial organization relationships among various types of travel behaviors and activity spaces of metropolitan residents. Ample evidences have suggested that residence and work are the most significant daily activities with strong spatiotemporal patterns (Liu et al., 2022; Sevtsuk & Ratti, 2010). As a result, researchers have mainly focused on the jobs-housing spatial relationship from the perspective of commuting flows or networks (Long & Thill, 2015; Odell et al., 2022; Zhang et al., 2017). For example, Odell et al. (2022) analyzed the changing structure of the Greater Manchester metropolitan area using 40 years of commuter flow data. However, the impacts of globalization and informatization have brought significant changes to residents' activities and travel patterns (Schwanen et al., 2008). With the advancements in ICTs and economic development, residents' living requirements and travel capabilities have greatly improved, and their travel behavior is no longer solely driven by survival needs. This occurrence has led to a certain degree of change in the travel pattern dominated by commuting behavior, and residents' travel behaviors and activity patterns are increasingly complex, diversified, and personalized (Liu et al., 2022). In this context, urban residents' non-home-working travel and activity spaces, as an integral part of urban life, deserve greater attention.

Second, while previous studies have performed many explorations on the spatial interaction relationship and network structure generated by human movement (Liu et al., 2014; Zhang et al., 2018; Zhang, Liu, & Senousi, 2021), these investigations tended to explore the UTNs based on travel flows without trip purpose or limited types of travel flows, few attentions have been paid to the intra-urban travel networks and urban structure under the perspective of multiple travel flows. For instance, Zhong et al. (2014) constructed a weighted directed network of Singapore based on smart card datasets and effectively identified the spatial structure of urban hubs, centers, and boundaries by integrating network and spatial analysis methods. They validated the projections from the network structure to urban structure in mobility networks. Nevertheless, the city is a multiplex system, and spatial interactions between areas can take many forms, such as commuting, shopping, and dining trips (Burger et al., 2014). Since multiple travel flows exist simultaneously within urban spaces and interact with each other, resulting in different UTNs, which may unveil the urban structure from different interaction perspectives (Zhang, Liu, & Senousi, 2021). For example, a city can appear to be polycentric and spatially integrated based on commuting linkages but monocentric and loosely connected based on the analysis of dining linkages. Consequently, evaluating urban structures based on single or limited types of travel networks is inadequate (Liu et al., 2020). Examining intra-urban travel networks from the perspective of multiple travel flows is crucial to portray and assess the urban spatial structure comprehensively.

Third, current studies lack a comprehensive and systematic research framework that integrates multi-source data and interdisciplinary approaches for inferring activity purposes and analyzing multiple travel networks. Traditional methods like transport travel surveys and resident activity log records are both costly and time-consuming, making it difficult to obtain large-scale, fine-grained human mobility information (Xu et al., 2021). Moreover, mobile phone data, floating vehicle data, and other trajectory big data lack explicit information about trip purposes and activity categories, thus limiting the scale and scope of human mobility and urban studies (Li et al., 2021; Liu et al., 2020). Some studies have attempted to infer activity and travel purposes using various data sources, including land-use data, point of interests (POIs), social media data, and street images, yielding important and effective results (Li et al., 2021; Liu, Huang, et al., 2021; Tu et al., 2017). However, due to the representativeness and bias of big data, most relevant studies have not been verified using actual resident activity and travel information, leading to inevitable limitations in the findings (Yin et al., 2021). Accordingly, analytical framework that can better integrate multiple data sources for travel flow extraction and network construction must be developed to tackle the increasingly complex relationship between travel networks and urban structures.

To fill the above research gaps, three specific research questions were proposed and answered in this study: (a) How can various residents' daily activities be identified through multi-source data fusion technologies to construct different UTNs? (b) What are the structural similarities and disparities among various UTNs from the perspective of multiple travel flows? (c) What urban structures are inferred and varying in different UTNs? To answer these questions, in this study, we proposed an analytical framework that integrates multi-source datasets and multidisciplinary approaches to explore the urban travel structure from the view of multiple travel flows. First, leveraging multi-source datasets collected in Beijing, we inferred the locations and types of daily activities for over four million residents by performing multi-source data fusion, resulting in a high-quality fine-scale urban travel flows dataset. Next, various UTNs were constructed based on multiple travel flows with distinct purposes. Subsequently, spatial analysis and complex network analysis methods were applied to explore the macroscopic characteristics of the UTNs, examine the importance of travel nodes, and analyze their spatial interactions. Finally, a community structure algorithm was utilized to uncover the urban community structures within the different UTNs. Ultimately, this study aims to provide a comprehensive scientific understanding and valuable insights into the urban spatial structure. The research findings can be leveraged to inform urban residents about daily travel, public facility configurations, and activity space optimization.

The remainder of this paper is organized as follows. Section 2 describes the study area and datasets used in this study. Section 3 explains the methodological framework and describes the corresponding methods in detail. In Section 4, we present the results of our analyses. We discuss the key findings and practical implications of our study in Section 5. Finally, the conclusions of this paper are drawn and future research directions are proposed in Section 6.

2. Study area and datasets

2.1. Study area

Beijing is a world-class metropolis and the capital of China, and it is also the political and cultural center of the country. The study area for our research encompassed the urban region within Beijing's Sixth ring road, which represents a highly urbanized and relatively homogeneous area (Fig. 1). According to the Beijing Transport Development Annual Report 2020 (Beijing Transport Institute, 2021), this study area accounted for approximately 80 % of the residential population and jobs in Beijing in 2020, making it a major area for population distribution and socioeconomic activities. However, Beijing is facing a developmental dilemma due to its high population density and limited space resources in the central city. Therefore, the Beijing Municipal Government is actively promoting the decentralization of the population and non-capital functions from the central urban district. This initiative aims to optimize the urban spatial structure and create a livable city environment. Thus, it holds immense theoretical and practical significance to conduct an in-depth study on the travel structure within the core urbanized areas of Beijing.

In this study, a hexagonal study unit with a spatial resolution of 1 km × 1 km was utilized. A hexagonal grid was selected because it covers an area with more regularly sized hexagonal cells than a raster grid. Moreover, hexagonal cells are closer in shape to circles than rectangular cells, and suffer from less orientation bias and sampling bias from edge effects than other cell shapes (Wang & Kwan, 2018). Finally, the study area contains 2385 units within the Sixth Ring Road (Fig. 1).

2.2. Datasets

Our study included four main datasets: mobile phone signaling, POIs, Sina Weibo (Chinese Twitter), and questionnaire datasets. The mobile phone data were the aggregated data of Beijing during May 2019, which were obtained from Smartsteps (www.smartsteps.com), a big data technology provider. The data included user personal attributes (gender and age), movement and stay information, details about stay type and frequency (e.g., residence, working, and visit), and other relevant information. The stay data included the location data of the first location in the morning and the last location in the evening, and location data for the rest of the time were recorded when multiple signals were triggered at the same location, and the starting and ending intervals were >30 min apart. Each location corresponded to a 100 m × 100 m grid, and changes from one location point to another location point were regarded as a movement (Liu et al., 2022).

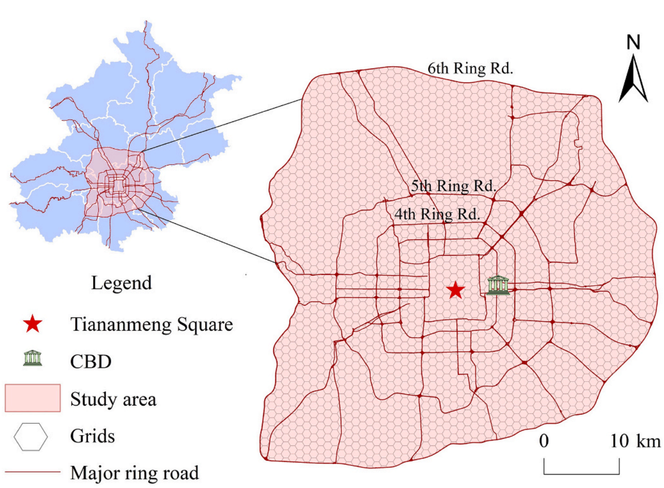

Fig. 1. Map of the study area, with grids and ring roads.
*Note: central business district (CBD); road (Rd).

The POI dataset used in this study was collected from AutoNavi Map (https://lbs.amap.com/), which contains nearly 0.9 million POIs within the study area. The attributes of each POI include the ID, name, longitude, latitude, and category. The data types of POIs include 23 different primary categories and hundreds of subcategories, such as dining, shopping, recreation, schooling, and life services.

Social media data contain detailed spatiotemporal, textual, image, social, and other multidimensional information about users and thus can provide powerful data support to reveal users' behavioral activity types and spatiotemporal characteristics efficiently. In a study by Liu, Huang, et al. (2021), Weibo data was subjected to text mining using natural language processing techniques and deep learning algorithms. They identified nearly 1.2 million Weibo data points related to the daily activities of Beijing residents, which were further categorized into seven activity categories: social, eating, entertainment, shopping, studying, sports, and working (Liu, Huang, et al., 2021). In this study, we employed this dataset combined with the abovementioned datasets to identify specific types of daily activities.

This study also utilized a questionnaire dataset on the daily activities of Beijing residents. The survey focused on capturing information about residents' homes, workplaces, and activities and was conducted in the urban areas of Beijing in December 2020. The survey received approval from the Department of Urban Science, Beijing Union University (Approval No. 2020BUU-011-15), and all participants provided informed consent. The survey covered 142 subdistricts within the Sixth ring road, and all participants were randomly selected from these subdistricts, and trained investigators conducted face-to-face questionnaire surveys. Given the coverage of multiple subdistricts, this survey is representative of the daily activities of urban residents in Beijing. The questionnaire dataset consisted of five parts: housing status (location and type), employment status (location and occupation), commuting characteristics (time, transportation modes, and other activities during commuting), daily activity information (high-frequency activity locations, types, frequency, time, travel, and transportation modes), and personal basic information of the respondents (gender, age, education, income, and family structure). A total of 907 questionnaires were obtained during the survey. After removing questionnaires with missing data, 762 surveys remained, resulting in an effective rate of 84.01 %. In this study, we specifically used two indicators, namely high-frequency activity locations and activity types, from the questionnaire data to verify the accuracy of activity category identification.

3. Methodology

Fig. 2 illustrates the analytical framework proposed in our study, consisting of four key parts: dataset collection and preprocessing, activity type identification, travel flow extraction and network construction, and network structure analysis. First, we collected the mobile phone, POIs, Weibo, and questionnaire datasets from various platforms. These datasets were subjected to rigorous cleaning and preprocessing procedures to eliminate noise and outliers. Second, we identified each mobile phone user's home, workplace, and major activity locations by analyzing their monthly stay time and frequency. Buffer zones were subsequently generated around these major activity locations, and specific categories of major activity spaces were determined by integrating the POIs and Weibo datasets. Third, the users' homes and activity spaces were linked to the grids by spatial join, and various travel flows between grids were extracted. Then, using the grids as nodes and the travel flows as edges, different UTNs were established. Finally, we employed spatial analysis techniques and complex network analytics to investigate the similarities and disparities among the various UTNs from multiple dimensions. By following this framework, we can gain valuable insights into the complex interplay between human activities, travel patterns, and urban spatial organization in Beijing.

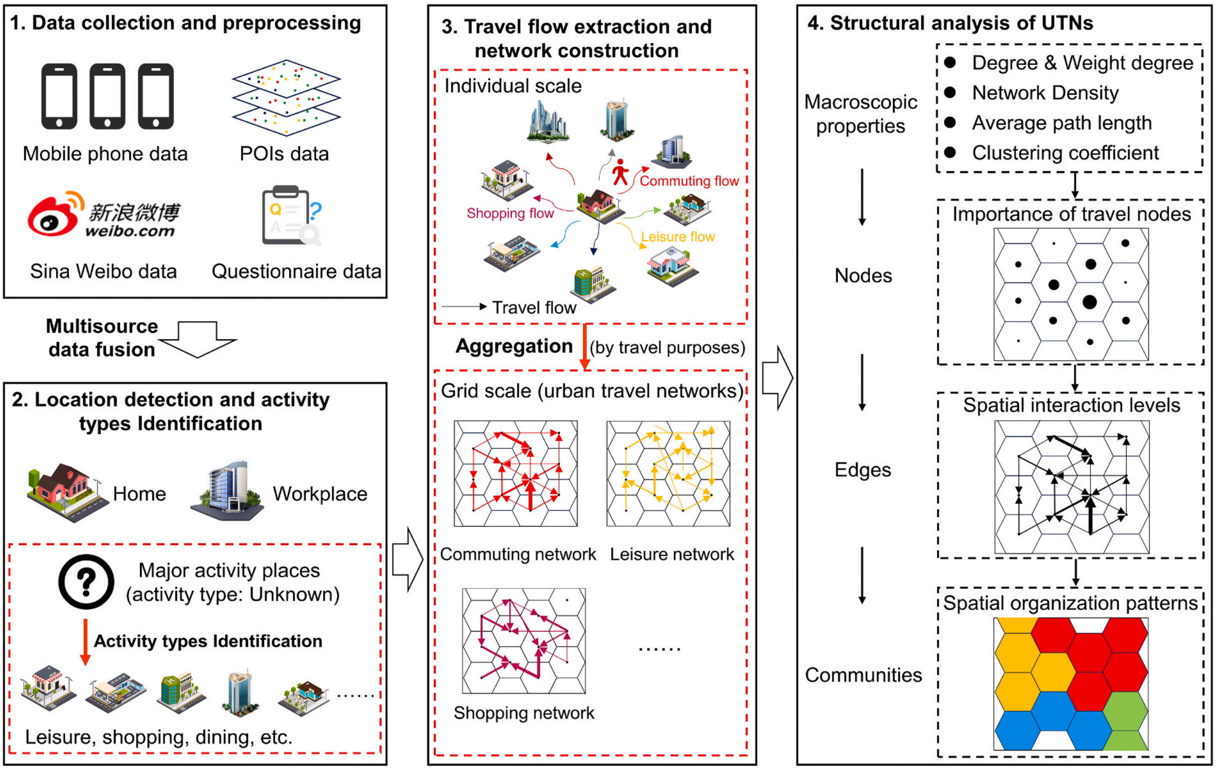

Fig. 2. Analytical framework of this study.

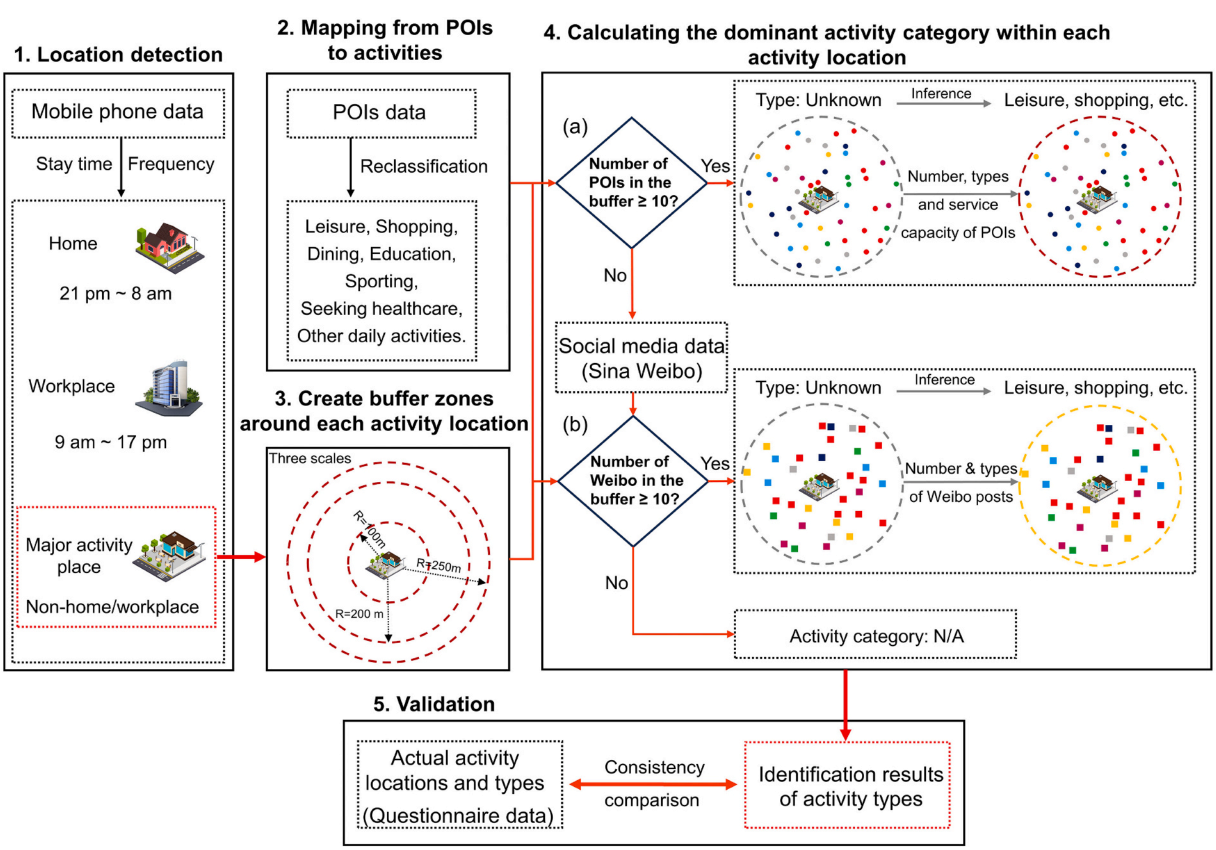

Fig. 3. Workflow of activity category identification.

3.1. Identification of activity categories

3.1.1. Home, workplace, and major activity place detection

Individuals usually travel from their homes to various activity locations in daily life. Homes and workplaces are the primary activity sites, exhibiting strong spatiotemporal regularity. Therefore, identifying homes and workplaces using mobile phone data has been well-established. This study adopted existing methods (Liu et al., 2022) to identify users' homes and workplaces based on stay time and frequency. Notably, we identified 4,011,571 local users within the study area, with 53.3 % having a stable workplace. This rate closely aligns with the overall employment rate in Beijing in 2019 (59.1 %) (Beijing Municipal Bureau of Statistics, 2020). Furthermore, we compared the identified homes of local users in each subdistrict with the populations reported in the Gazette of the Seventh National Population Census for the Beijing Municipality. The analysis revealed a high correlation coefficient of 0.776 ($p < 0.01$) between the mobile phone data and official statistics, affirming the representativeness of the identified user information.

Subsequently, we identified other frequently visited locations of residents (at least five visits per month with a minimum stay time of 0.5 h per visit) as major activity spaces. However, since the mobile phone dataset lacks information about users' specific travel purposes, the specific types of user activities remain unknown. Previous studies have shown that POIs visited by individuals contain a wide range of human activities, such as dining, traveling, and shopping. Therefore, we leveraged the POI information to infer the activity categories of residents (Li et al., 2021; Xing et al., 2020). Additionally, in areas with sparse POI data, we supplemented the analysis with Weibo data, which contains valuable information about human activities. To validate the accuracy of our method, we employed questionnaire data, which provided actual activity locations and types. The proposed activity inference method is illustrated in Fig. 3, outlining the workflow of our approach.

3.1.2. Mapping the relationship between activity categories and related POI types

As mentioned in Section 2.2, the original dataset of POIs contained various types, including some less informative categories such as Auto Service, Road Furniture, Place Name & Address, etc. To enhance the relevance and informativeness of the POIs, we reclassified and mapped them into activity categories, referring to previous studies in the field. Specifically, considering residents' daily behavioral patterns and drawing insights from existing research (Li et al., 2021; Liu, Yan, et al., 2021), we established a mapping relationship between different activity categories and corresponding POI types. In this study, we focused on seven basic daily activities that people engage in: leisure, shopping, dining, education, sporting, seeking healthcare, and other daily activities. The mapping of POIs to activity categories is presented in Table 1.

Additionally, a recent study by Li et al. (2021) demonstrated that incorporating the type proportion and service capacity of POIs can enhance the effectiveness of models for inferring trip purposes. The service capacity index represents a metric used to quantify the capacity or potential of a specific POI type to serve particular activities. The values in the service capacity index can be interpreted as relative weights assigned to each POI type based on its capability to accommodate certain activities. Higher values indicate a higher capacity or suitability of the POI type for supporting the corresponding activity category. By assigning different weights to each POI type, we can assess the probability of a specific activity category being dominant in each location. Therefore, in this study, we adopted the service capacity index of POIs proposed by Li et al. (2021) to support the subsequent identification of activity types. Table 1 provides an overview of the service capacity for various POIs.

Table 1
Mapping the relationship between activity categories and related POI types as well as the service capacity index of each POI category.

Activity categories	POI types	Service capacity index	Number
Leisure	Parks and squares	0.82	1053
	Exhibition halls and exhibition centers	0.92	1762
	Sports and leisure service places, vacation village	0.81	4654
	Entertainment places, and golf venues	0.73	3881
	Scenic spots	0.59	4268
	Art museum, art groups, theaters, science and technology museum, planetarium, leisure, bathing, and massage places	0.44	3278
	Museums, archives and cultural palaces	0.39	673
	Teahouses, café, and casual dining venues	0.18	4438
Shopping	Shopping malls, commercial streets, and comprehensive markets	0.77	8024
	Building material markets	0.56	18,676
	Electronic stores, flower, bird, fish, and insect markets	0.47	10,169
	Supermarkets, convenience stores, clothing, shoes, hats, leather goods stores, personal goods, cosmetics stores, exclusive stores, cultural stores, and sports stores	0.3	79,366
Dining	Chinese restaurants, foreign restaurants, and fast food restaurants	0.43	52,913
	Desserts, cold drinks, pastries, and other dining related places	0.18	3942
Education	Colleges and universities	0.97	1728
	Library	0.97	478
	Primary school, middle school, high school, and kindergarten	0.43	5859
	Training institutions	0.29	10,961
	Scientific and educational places	0.24	21,342
Sporting	Stadiums and sporting grounds	0.5	6486
Seeking healthcare	General hospital, special hospital, emergency center, vacation and recreation sites, and sanatoriums	0.65	5464
	Disease prevention institutions, medical and health care service places, Clinics, health and care stores	0.31	9212
Other daily activities	Electric communication, electric power, water business hall, business hall, and post office	0.47	2868
	Logistics express	0.33	5088
	ATM, bank, baby service, photography and printing shop, laundry, tourist agency, beauty salon, and lottery ticket sales points	0.23	40,735

3.1.3. Creating buffer zones around each activity site

Next, we extracted all activity sites based on the mobile phone data, with each site represented by a 100 m × 100 m grid. Subsequently, three buffer zones around each activity location were established, with radii of 100 m, 200 m, and 250 m, to obtain candidate POIs. All the POIs within these buffers (i.e., within 100 m, 200 m, and 250 m of the activity location) were considered as candidate POIs for inferring the corresponding activity category.

3.1.4. Calculating the dominant activity category within activity locations

Furthermore, we designed two scenarios to calculate the dominant activity category within activity locations.

Scenario One (Fig. 3(a)): For buffers containing more than ten POIs, we employed a basic model to assess the attractiveness of each POI type within the activity location. This calculation considered the POI type, quantity, and service capacity. The types and numbers of POIs within the buffers were counted by spatial join. The probability of each activity type within a buffer was then calculated using the following formula:

$$P_i = \frac{\sum_{j=1}^{n} S_j N_j}{\sum_{i=1}^{i=7} \sum_{j=1}^{n} S_{ij} N_{ij}} \tag{1}$$

where *i* represents the seven categories of activities corresponding to the major categories of POIs, with a value range of 1–7; P_i denotes the probability of activity type *i* in the buffer; *j* represents the subcategory of POIs; *n* is the type number of the POI subcategory; S_j and N_j denote the service capability index and number of the subcategory POIs of *j*, respectively; S_{ij} and N_{ij} represent the service capability index and the number of the subcategory POIs of *j* in the major category POIs of *i*, respectively.

According to Eq. (1), we calculated the probability of each of the seven activity types corresponding to the POIs in each buffer, based on which we selected the activity type with the highest probability in the buffer as the dominant activity type (*A*) in that buffer. The calculation formula of *A* is as follows:

$$A = Max\{P_i\}, i \in [1, 7] \tag{2}$$

Scenario Two (Fig. 3(b)): In cases where the number of POIs within a buffer was extremely low (less than ten), we considered the Weibo data within the buffer. The Weibo data used in our study contains specific activity types of residents. Like inferring activity types from POI data, we calculated the proportion of Weibo-based activity within each buffer. The activity type with the highest proportion was considered the dominant activity type (*A*) within that buffer.

However, if both the number of POIs and Weibo items within a buffer were less than ten, the activity type for that area was considered unavailable (N/A).

3.1.5. Validation

Finally, as mentioned above, the questionnaire dataset utilized in our study contains detailed information about residents' daily activities, including the locations, types, and frequency of their activities. Accordingly, we applied the activity identification method outlined in this paper to infer the activity types for all survey respondents. Subsequently, we compared the inferred activity types with the actual survey results to assess their consistency and verify the accuracy of our activity classification method.

3.2. Construction of travel networks

Using the aforementioned method for identifying activity types, we identified several categories of resident activities, including leisure, shopping, and dining. As a result, each resident's daily living circle can be established, where their home serves as the center and activity locations act as endpoints (Fig. 4). Then, we generated various types of travel flows by considering the residents' homes as the origin and their activity sites as destinations. To transform individual travel flows into connections between different geospatial units (grids), we superimposed the various travel flows of each resident with the grid system. The travel flows of millions of residents, categorized by different travel purposes, were then aggregated within the grids. Utilizing network analysis techniques, we established eight directed weighted UTNs: commuting network (CN), leisure network (LN), shopping network (SHC), dining network (DN), education network (EN), sporting network (SPN), seeking healthcare network (SEN), and other daily activities network (ON). Considering the spatial and topological characteristics of these UTNs, we

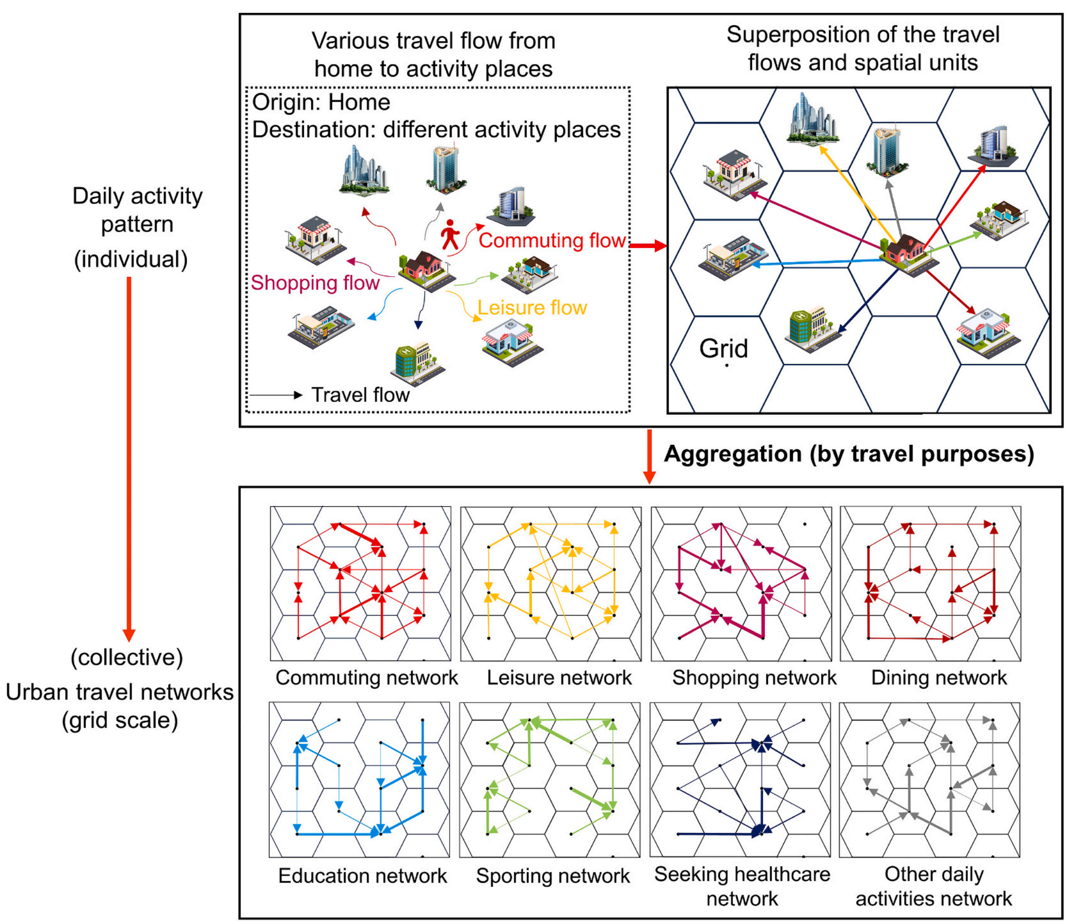

Fig. 4. An illustration of the UTNs construction.

developed a comprehensive analytical framework to explore the structural characteristics and their similarities and disparities from multiple dimensions.

3.3. Structural analysis of UTNs

3.3.1. Macroscopic characteristics of the UTNs

UTNs are special complex networks with spatial embedding, thus, they have complex network and general spatial constraint characteristics (Wang, Deng, et al., 2020). In this section, we analyzed UTNs from the macroscopic statistical perspective. The specific metrics are as follows:

- Degree: the number of relations (edges) of a node, which denotes how many areas are directly connected to an area from any other.
- Weight degree: the sum of weights of a node, which indicates the intensity of travel (trip volumes) to and from one area;
- Network density (ND): the ratio of the actual number of edges in the network to the maximum number of possible edges, which is used to represent the overall connectivity within the network;
- Average path length (AL): the average number of steps along the shortest paths for all possible pairs of network nodes (Albert & Barabási, 2002);
- Clustering coefficient (C): measures the degree to which nodes in the networks tend to cluster together, which shows how well the neighbors of a node are connected to each other (Fagiolo, 2007).

3.3.2. Weight degree centrality: the importance index of travel nodes

Centrality reflects the influence and importance of nodes within a network, and its applications include identifying critical infrastructure nodes in Internet and urban networks and quantitatively assessing the node importance (Wang, Yue, et al., 2020). In UTNs, a high-centrality node indicates a transportation hub that bears more daily transit and activities, and such nodes also help to describe the urban structure (Zhang, Liu, & Senousi, 2021). With the diversity of centrality measures in complex networks resulting from different definitions of importance (Kang et al., 2022). Among them, weighted degree centrality (WDC) incorporates connectivity and edge weights, making it particularly suitable for networks with weighted edges. Considering the characteristics of spatial interaction networks formed by daily travel flows and the variability and directionality of travel flows among spatial units, we employed WDC to quantify the importance of nodes in different UTNs. In this study, the WDC of an arbitrary node was defined as the sum of the weights of its associated edges. A higher WDC indicates stronger external attraction and radiation from the spatial node. However, due to the large difference in the size of the travel flows across different purposes, the network size varies among UTNs. As a result, the relative difference in the importance of the same node in different networks cannot be reflected by absolute WDC. To address this, we employed the min-max normalization method (Henderi, 2021) to calculate the relative WDC (RW), enabling a meaningful horizontal comparison of the relative importance of travel nodes across various UTNs. The calculation of RW is as follows:

$$RW_{i,j} = \frac{W_{ij} - min(W_j)}{max(W_j) - min(W_j)} \tag{3}$$

where $RW_{i,j}$ denotes the relative importance of node i in network j; W_{ij} is the WDC of node i in network j; $min(W_j)$ and $max(W_j)$ represent the minimum and maximum WDC in network j, respectively. A larger RW indicates higher relative importance of the node in UTNs.

3.3.3. Classification of spatial interaction levels

Flows in UTNs provide valuable information about the direction and intensity of interactions between spatial nodes within a city. To capture the degree of spatial interactions, we counted the number of travel flows between spatial nodes in each UTN, serving as an indicator of spatial interaction level. Then, the travel flows in UTNs were divided into three levels (high, medium, and low) based on the Jenks Natural Breaks method, offering insights into the hierarchical distribution of spatial interactions within the eight travel networks.

3.3.4. Community structure detection of UTNs

Community structures play a significant role in understanding the organizational patterns of nodes within a network, with tight groups exhibiting high within-group edge density and low between-group edge density (Wang, Yue, et al., 2020). Community detection of UTNs is beneficial for revealing well-connected groups and their spatial patterns. It not only reflects the connectivity of spatial units but also reveals the extent to which these communities align with the administrative spatial divisions of the city, shedding light on the presence of independent functional areas (Yuan et al., 2015). Additionally, detecting community structures based on urban daily travel flows provides important guidance for optimizing the configuration of public transportation facilities and improving the accessibility to activity spaces. To unveil community structures and geospatial patterns within different UTNs, we adopted the 'Fast Unfolding algorithm' proposed by Blondel et al. (2008). This algorithm maximizes network modularity and identifies community structures through a bottom-up hierarchical clustering approach. Owing to its accuracy and efficiency, it has been widely used in relevant studies (Lancichinetti & Fortunato, 2009; Liu et al., 2023). Thus, we employed this algorithm to detect the community structures of UTNs in our study.

4. Results

4.1. Spatial distribution of residents' daily activities

Based on our proposed activity category identification method, we inferred activity types using buffer sizes of 100 m, 200 m, and 250 m, respectively. The accuracy of these inferences was verified using the questionnaire data, as described in Section 3.1.4. Our results show that the highest recognition rate and accuracy were achieved when inferring activity types using the 100 m buffer scale. Specifically, we identified 86.2 % of residents' daily activity types with a precision of 76.5 %. This result demonstrates the overall effectiveness of the activity type identification method employed in this study, validating its utility for subsequent studies.

Kernel density estimation (KDE) is a widely used technique for detecting point pattern and visualizing spatial agglomeration characteristics and distribution patterns of activities (Liu, Meng, et al., 2021). In this study, KDE was used to explore the spatial distribution patterns and hotspot areas of Beijing residents' daily activities, as shown in Fig. 5. The spatial distribution of daily activities is uneven, and various types of residents' activities have distinct spatial clustering and polycentric characteristics. Multiple spatially clustered areas are observed for each activity category, varying in number and scale. Notably, working, home, and leisure activities exhibit high densities and form several large clusters. Shopping, dining, and educational activities also demonstrate relatively high densities, with concentrated high-level activity clusters. Conversely, seeking healthcare, sporting, and other daily activities exhibit lower densities, with fewer activity clusters and a dispersed spatial distribution.

4.2. Macrostructural characteristics of UTNs

Table 2 presents seven macroscopic characteristic parameters for the eight UTNs, including the number of nodes (N), edges (E), average degree (AD), average weighted degree (AWD), ND, C, and AL. In terms of network completeness and connectedness, CN exhibits higher indicators (except for AL) than other UTNs, indicating its superior completeness and degree of connection, followed by those of SHN, LN, DN, EN, ON, SEN, and SPN. Regarding network clustering, the average clustering

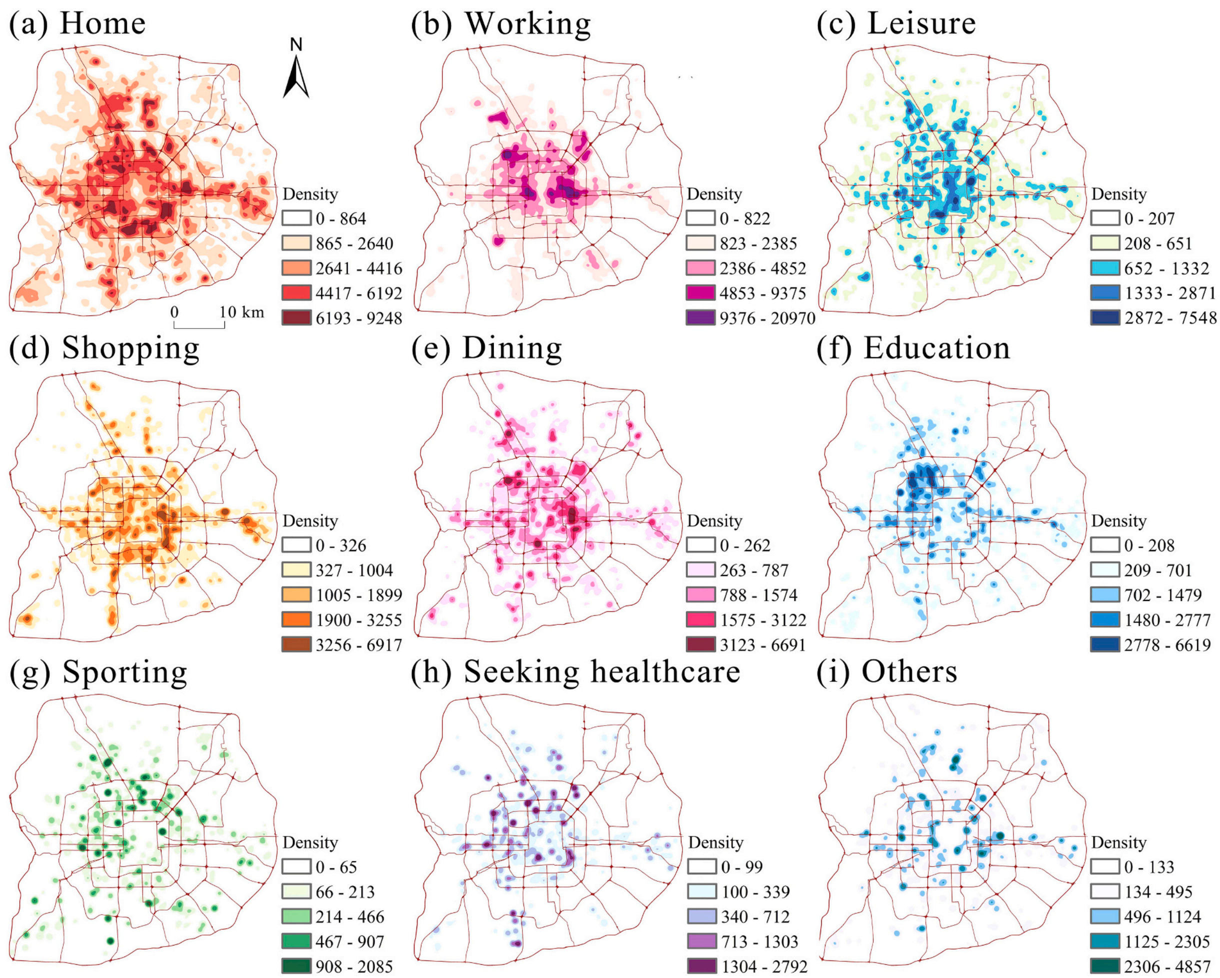

Fig. 5. Spatial distribution of the daily activity space of Beijing residents.

Table 2
Macroscopic properties of UTNs.

Properties	CN	LN	SHN	DN	EN	SPN	SEN	ON
N	2333	2299	2284	2289	2283	2212	2149	2197
E	635,405	238,276	252,491	223,668	190,417	58,232	61,189	86,438
AD	272.36	103.64	110.55	97.71	83.41	26.33	28.47	39.34
AWD	20,054.85	3085.21	4094.49	3052.93	2625.01	619.29	779.73	1130.62
ND	0.117	0.045	0.048	0.043	0.037	0.012	0.013	0.018
C	0.38	0.25	0.34	0.3	0.28	0.18	0.25	0.26
AL	2.01	2.34	2.38	2.36	2.44	2.99	2.51	2.46

coefficients of UTNs range from 0.2 to 0.3, indicating high interconnectivity and clustering among most nodes in each UTN. Moreover, CN has the shortest AL (2.01), while SPN has the longest (2.99), suggesting that all UTNs exhibit average delivery efficiency, with most spatial nodes requiring at least one transit node to establish contact, resulting in relatively low overall accessibility.

To visualize the geospatial structure of the eight UTNs, we utilized the geographic visualization tool—Flowmap (Fig. 6). In the figure, the nodes represent activity locations, and their size corresponds to the volume of the activities. The edges denote spatial interactions between the nodes, with the thickness of the edges indicating the strength of the interactions. As depicted in the figure, the overall structure of each UTN demonstrates a dominance of centripetal flows, forming several major activity centers within the central city, thus displaying a significant polycentric structure. Comprehensive business districts, popular attractions, higher education institutions, and large sports venues that attract dense populations and socioeconomic activities tend to be important network nodes in UTNs. Examples include Shangdi, Beijing Workers' Stadium, Taikoo Li Sanlitun, Zhongguancun Science Park, and Olympic Forest Park. Furthermore, each UTN exhibits a hierarchical distribution pattern, with higher-level spatial nodes and interconnections concentrated in the central city, while the suburbs contain lower-level nodes and interconnections. These characteristics highlight the significant spatial hierarchy and heterogeneity present within the UTNs.

4.3. Polycentric hierarchical distribution of node importance in UTNs

We calculated travel nodes' relative importance index (RW) in different UTNs using the method described in Section 3.3.2. The RW values were categorized into five levels: lowest, lower, medium, higher, and highest. The spatial distribution of RW for the various UTNs is

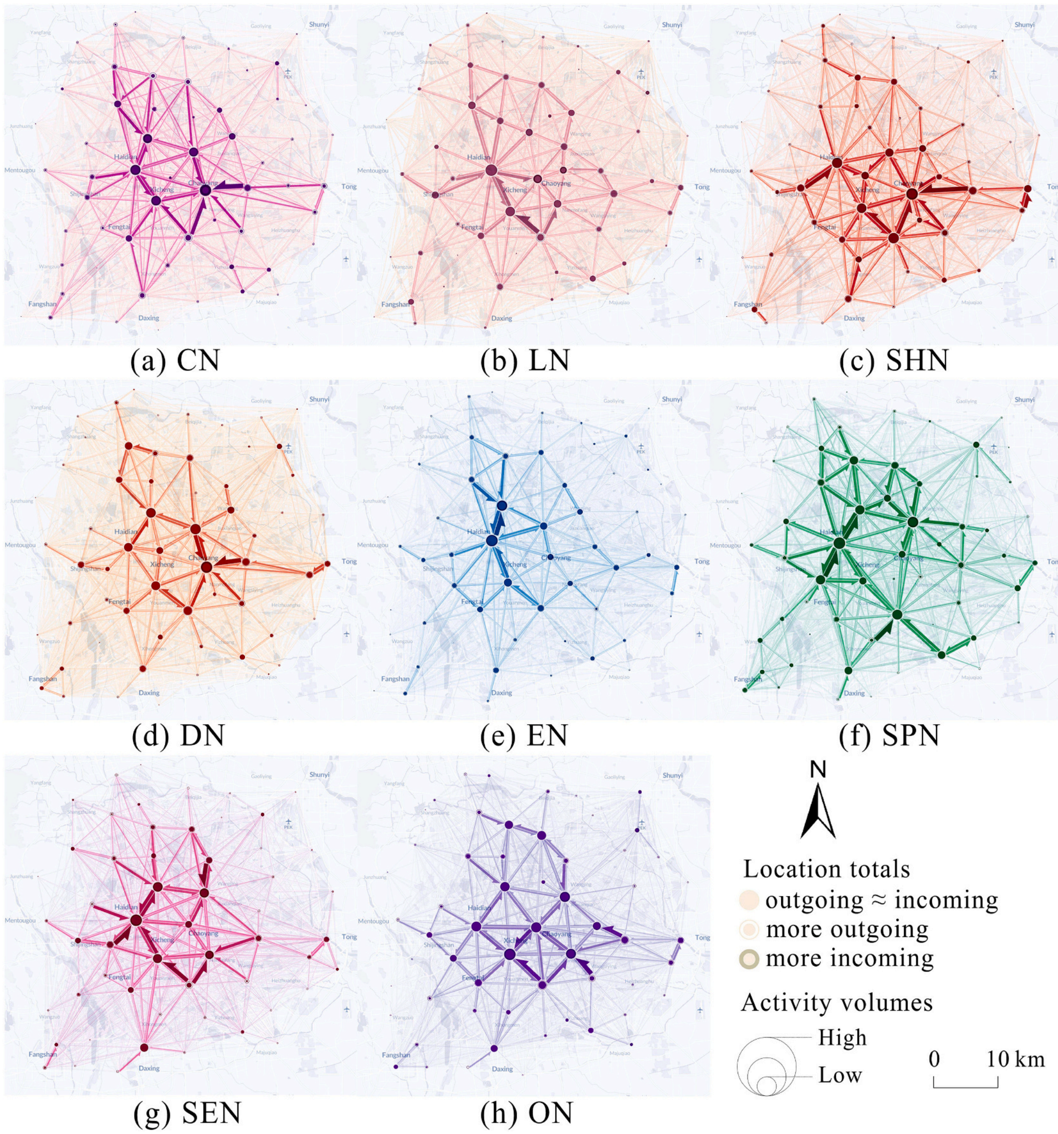

Fig. 6. Geospatial structure of the UTNs.

presented in Fig. 7. Overall, a significant polycentric hierarchical pattern can be observed regarding node importance. There are several high-level important nodes in each UTN, but their number decreases as node importance increases, and most spatial nodes have low importance. Specifically, CN, LN, SHN, and DN exhibit similar spatial distributions, characterized by a core-periphery structure. Nodes in the central city are generally of higher importance, forming high-level clusters, while nodes outside the Fifth ring road have relatively low importance. In contrast, the node importance of EN, SPN, SEN, and ON varies significantly, influenced by the spatial distribution of corresponding activity facilities and demonstrating strong spatial dependence. Notably, EN shows prominent clustering characteristics, particularly in the Haidian district, along North West Third Ring Road and College Road.

Additionally, we analyzed the correlations among the importance of spatial nodes in different UTNs by calculating the Pearson correlation coefficient. The results are shown in Fig. 8. There is a positive correlation ($p < 0.001$) among the importance of spatial nodes within all eight UTNs. Among the interrelationships of the UTNs, CN exhibits the highest correlation with the other seven UTNs, with the following ranked correlation coefficients: CN∪DN (0.84), SHN∪CN (0.77), EN∪CN (0.74), LN∪CN (0.73), ON∪CN (0.62), SEN∪CN (0.55), and SPN∪CN (0.45). These results indicate that the important nodes in CN tend to be significant in the other UTNs as well, suggesting a tendency for individuals to engage in additional daily activities, particularly dining and shopping, near their workplace. Conversely, the correlations between the other seven UTNs and SPN are relatively low, with an average correlation coefficient of 0.386. It implies that people are less influenced by other daily activities and distance factors when participating in sporting activities.

4.4. Hierarchical clustering characteristics of spatial interactions in UTNs

Fig. 9 shows the spatial distribution of spatial interaction levels in UTNs. UTNs exhibit a limited number of high-level interactions, while most spatial interactions between travel nodes are low. Furthermore, geographically adjacent nodes demonstrate relatively high spatial interactions, aligning with Tobler's law, the first law of geography. In particular, CN stands out with an overall higher level of spatial interaction, especially in terms of medium- and high-level interactions, surpassing other UTNs. Notably, high-level spatial interactions in CN are concentrated around major employment centers such as the CBD, Zhongguancun Science Park, Advanced Business Park, Shangdi, and Yizhuang.

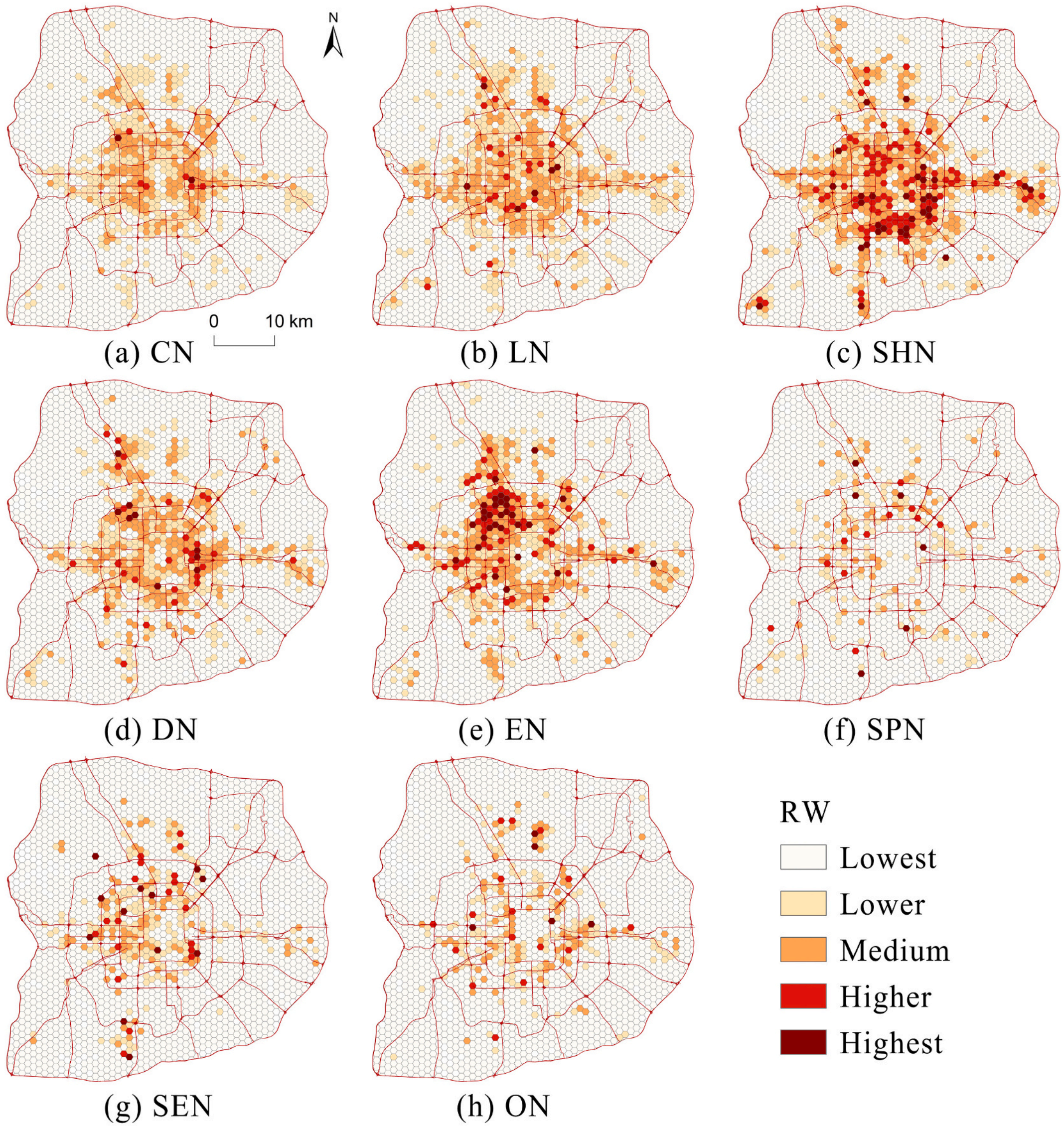

Fig. 7. Spatial distribution pattern of the RW of UTNs.

Moreover, the distribution of spatial interaction levels in LN, SHN, DN, and ON is similar, forming travel flow clusters around important business districts, large scenic spots, and key transportation hubs. These clusters include the CBD, Beijing Workers' Stadium, Taikoo Li Sanlitun, Zhongguancun Science Park, Wukesong, and Olympic Forest Park. Additionally, EN, SPN, and SEN exhibit diverse spatial distributions of spatial interactions. In the Haidian district, where colleges and universities are concentrated, high-level education interactions are primarily concentrated, particularly in the North West Third Ring Road and College Road areas. In SPN, several small sporting flow clusters emerge, connecting adjacent areas or spanning one to two spatial units. Conversely, healthcare-related spatial interactions are observed across multiple spatial units, heading towards large general or specialized hospitals such as Peking University Third Hospital, Peking University People's Hospital, Anzhen Hospital, and Beijing Cancer Hospital. Overall, these results shed light on the spatial interaction patterns within UTNs, highlighting the clustering characteristics of different levels and types of spatial interactions in specific areas.

4.5. *Community organization structure of UTNs: Sector model*

The community structures of the eight UTNs were explored using a community detection algorithm, and the corresponding statistical results are presented in Fig. 10. The UTNs are divided into six to ten communities, with SEN having the highest number of communities (ten) and CN having the lowest (six). Analyzing the clustering coefficients, the UTNs ranked as CN > SHN > DN > EN > ON>SEN > LN > SPN. Conversely, the maximum modularity of the UTNs followed the order: SPN > SEN > ON > SHN > DN = EN > LN > CN. When considering the average clustering coefficient and maximum modularity, CN shows the highest average clustering coefficient, but the lowest maximum modularity and the fewest number of communities. These indexes indicate that the community structure of CN is not prominent, with relatively weak intra-community connections. However, the connections between different communities are relatively strong, which may be attributed to the imbalanced job-housing distribution and long-distance commuting in Beijing. In contrast, SPN exhibits the lowest average clustering coefficient and the highest maximum modularity, indicating a robust community structure with greater intra-community connectivity and fewer long-distance trips for sports activities across multiple areas. Overall, our analysis reveals that larger UTNs tend to have higher average clustering coefficients and stronger regional connections, while exhibiting a less distinct community structure.

Fig. 11 illustrates the geographic distribution patterns of community

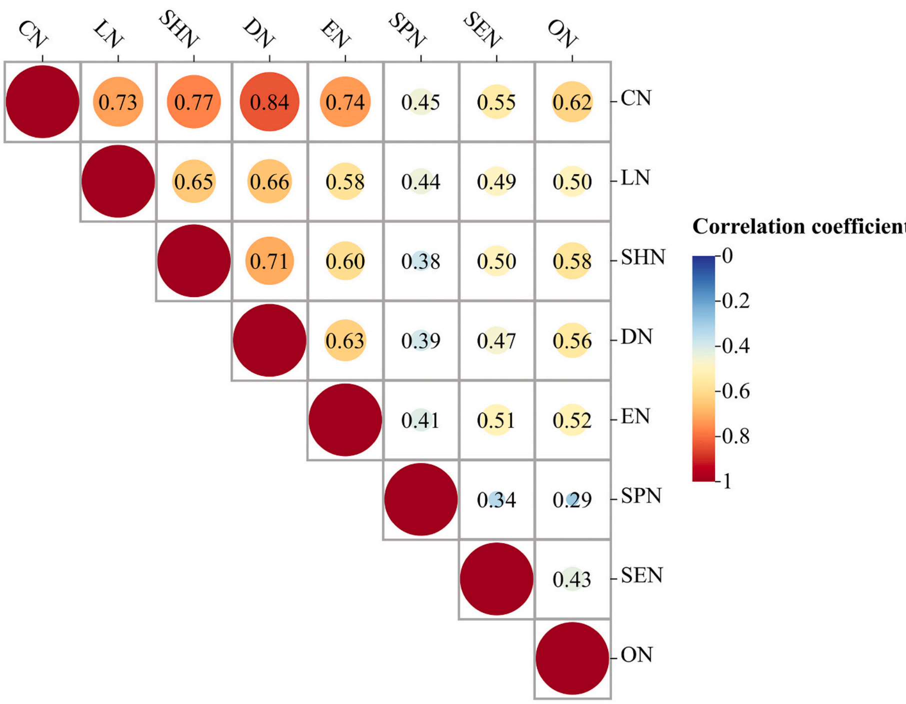

Fig. 8. Correlation matrix of the node importance of the UTNs.

organizations within the eight UTNs. The colors represent different communities, and the white lines denote administrative boundaries. As observed in Fig. 11, the community distribution characteristics of the UTNs exhibit a notable spatial agglomeration pattern, sharing similarities among the different UTNs. Despite the community detection algorithm used in this study not explicitly considering the geospatial relationship between nodes, the results reveal that most spatially proximate nodes tend to belong to the same community. Within a community, nodes are well-connected, but their connections to other communities in the network are comparatively weaker. In essence, the community organization within UTNs demonstrates an apparent geographic proximity effect. Among the UTNs, the community distribution characteristics of the first five (CN, LN, SHN, DN, and EN) display relative similarities, whereas SPN, SEN, and ON exhibit some deviations from the former group. Additionally, the community structures of the initial five networks demonstrate better organization, while the latter three networks appear relatively scattered. These distinctions can be attributed to the unique characteristics of each travel type. For instance, healthcare-related travel often deviates from the proximity principle and tends to involve detours, resulting in a more dispersed community organization in SEN.

Moreover, when comparing the community boundaries of each UTN with the existing administrative boundaries, significant spatial disparities can be observed. This indicates a notable mismatch between the current urban administrative divisions and the functional zoning based on actual residential travel behaviors. Furthermore, each UTN's community structure displays a corridor effect, wherein most spatial units along the ring roads belong to the same community and are interconnected by major roads within that community. Meanwhile, due to the distribution of transportation routes and the strong attraction of residents' activities in the central city, multiple communities emerge in each UTN, pointing towards the central city, and the spatial organization structure of communities corresponded to a sector model.

5. Discussion

5.1. Key findings

By reviewing the existing literature, although empirical evidence has been presented to understand the spatial interaction relationship and network structure shaped by human mobility, most focused on the UTNs from the perspective of single or limited types of travel flows. In this study, we took the central city of Beijing as a case study and employed multi-source data fusion techniques and network analytics to quantify the spatial organization and interaction patterns of residents' daily activities. By examining multiple travel networks, this work provided a comprehensive understanding of the intra-urban travel structure of Beijing. Our key findings are as follows:

First, we effectively identified eight distinct categories of daily activities among millions of Beijing residents through multi-source data fusion. The distribution of these activities exhibits a clustered and polycentric pattern, consistent with previous studies on the polycentric distribution of residence and employment in Beijing (Huang et al., 2017; Liu, Meng, et al., 2021). Building upon these prior findings, our study further reveals the polycentric structural characteristics of various types of residents' daily activities and examines their similarities and disparities. Furthermore, our study demonstrates a notable socio-spatial differentiation in the spatial distribution of residents' daily activities, with a significantly higher density observed in the central and northern areas compared to the southern region of the city. This disparity can be attributed to the development gap between the northern and southern parts of central Beijing (Liu et al., 2022; Liu, Huang, et al., 2021).

Second, as described in Sections 4.2 to 4.4, we conducted a comprehensive analysis of the spatial characteristics of various UTNs in terms of global structure, node importance, and spatial interaction levels among nodes. Our findings reveal that all UTNs exhibit significant spatially heterogeneity, hierarchical, and dependency. In terms of spatial nodes and their interactions, the distribution of node importance and interaction levels across UTNs follows a pyramidal hierarchical pattern. This pattern indicates that a small number of high-level spatial nodes and edges have a considerable influence and control over the UTNs, despite their limited quantity. These results collectively highlight

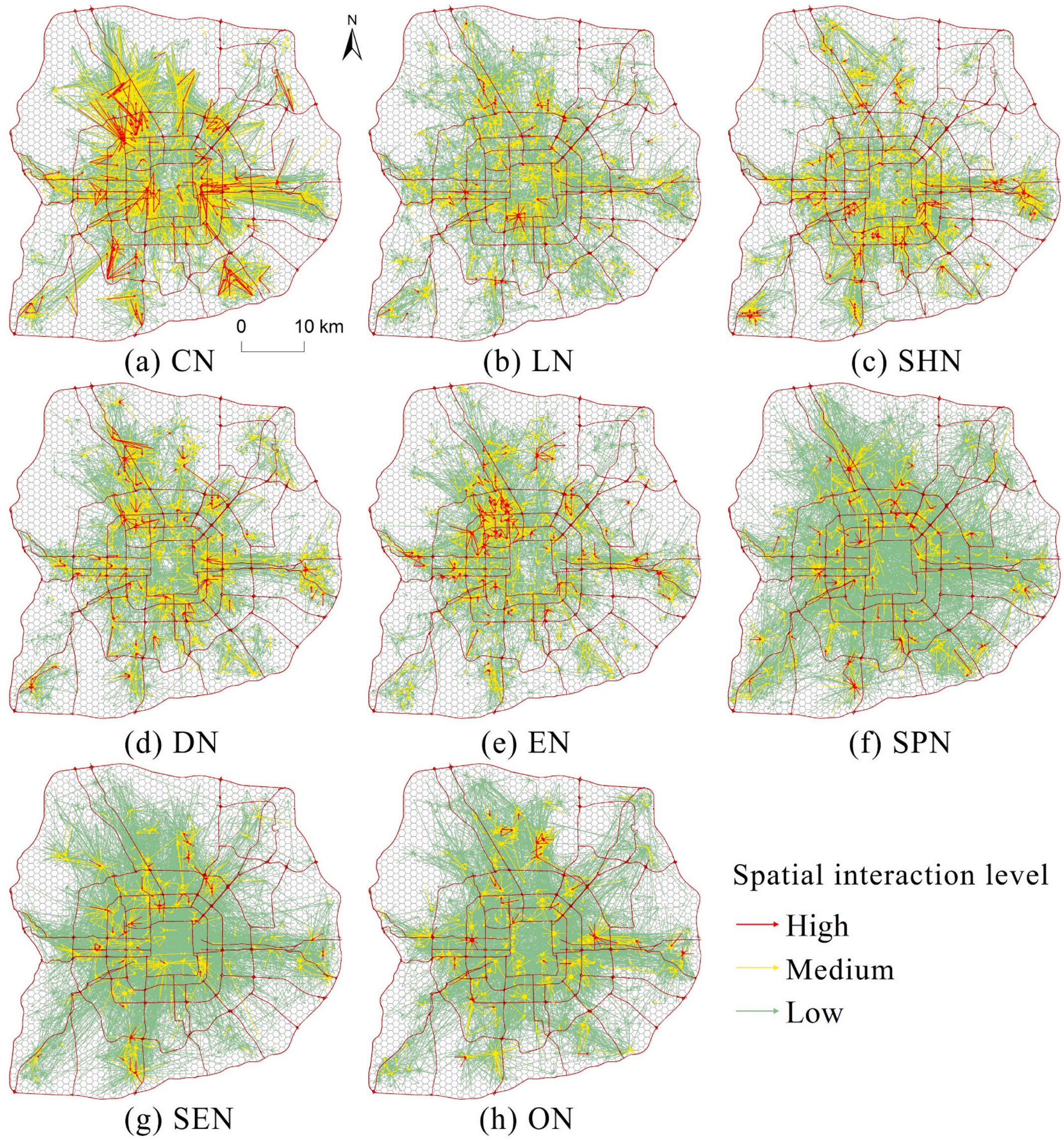

Fig. 9. Spatial distribution of spatial interaction levels in UTNs.

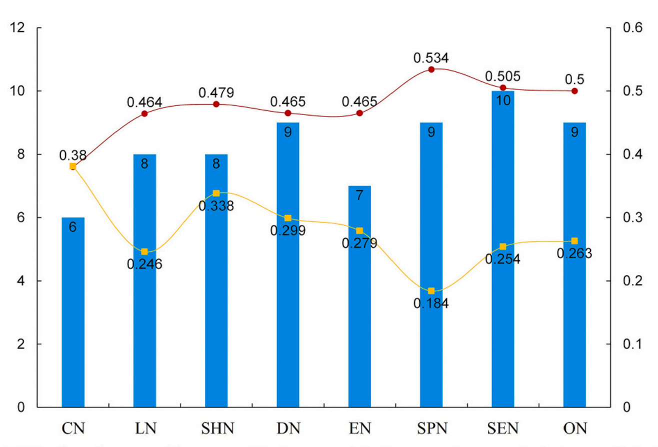

Fig. 10. Statistical results for the community detection of UTNs.

the polycentric hierarchical distribution pattern characterizing the urban structure of Beijing. Notably, this finding aligns with the polycentric urban development observed in other international metropolises, such as London (Zhang, Marshall, et al., 2021), Singapore (Zhong et al., 2017), and Tokyo (Aoki et al., 2023). Moreover, building upon previous studies (Burger et al., 2014; Yu et al., 2022), our study comprehensively unveils the functional polycentric structure of different UTNs in Beijing, providing insights into their similarities and disparities across various dimensions, including density, flow, and network.

Third, our study demonstrates that most communities within UTNs exhibit geographical cohesion and dense interconnections facilitated by various travel interactions. Furthermore, the spatial organization of these communities within each UTN forms a pattern of multiple sectoral clusters pointing towards the central city. The result suggests the existence of a functional sector model in Beijing. This finding differs from the situations of the polycentric structure of Beijing in previous studies (Liu, Meng, et al., 2021; Sun, 2020). Additionally, previous research suggested that the detected communities in the geographic space generally show some correspondence with top-down administrative borders, or multiple administrative districts integrated into each other and formed more closely connected community organizations (Liu, Yan, et al., 2021; Odell et al., 2022; Yin et al., 2017; Zhong et al., 2014).

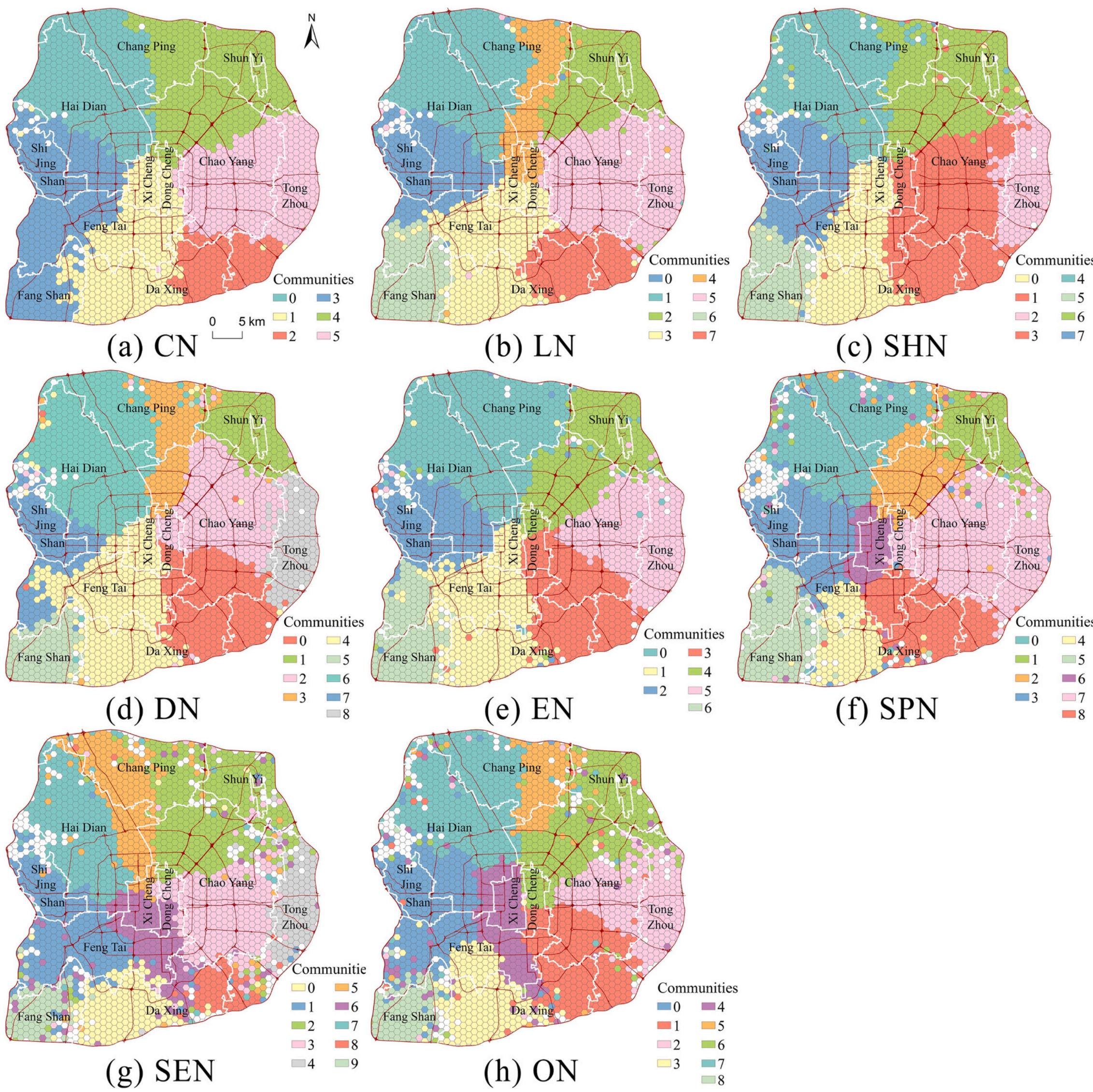

Fig. 11. Geographic distribution pattern of communities of UTNs.

However, unlike the above studies, substantial differences between community boundaries of UTNs and administrative unit boundaries can be observed in our study. This discrepancy highlights the substantial disparity between the actual spatial functional zoning formed by residents' daily travel and the existing administrative divisions. Interestingly, a similar finding was observed in a Shanghai-based study conducted by Wang, Yue, et al. (2020), suggesting that functional urban subdivisions do not necessarily align with administrative divisions. These empirical findings call for policymakers to reconsider whether administrative planning during urban development adequately reflects spatial interaction patterns or merely represents a top-down imposition.

5.2. Practical implications

The primary significance of this study lies in two aspects. Academically, we introduced an innovative research perspective by presenting an integrated urban travel structure assessment framework from a multi-activity view. This framework can unveil the urban spatial structure more accurately and comprehensively from the perspective of multiple travel flows. Consequently, our study not only comprehensively uncovers the holistic and systematic characteristics of urban travel structure, but also serves as a valuable supplement to current studies on human mobility and urban structure. Furthermore, by integrating multi-source datasets, including both big and small data, we overcome the challenges associated with the lack of semantic information in mobile phone data and the inconsistent identification and verification of various datasets. This integration enables us to achieve precise identification of residents' daily travel purposes and extract a high-quality intra-urban fine-scale resident travel dataset. This dataset provides a good database for human behavior and urban space studies. Moreover, this framework is based on spatial analysis methods and complex network analytics that are simple and universal, making it repeatable and easy to apply in other cities. In future studies, this methodology can be easily extended to other cities for human mobility and urban space studies, thereby providing methodological support for the broader field of urban science.

In practice, the findings in this study have several policy implications. **First**, our study reveals that all the UTNs exhibit a polycentric hierarchical distribution pattern. Considering polycentric urban development significantly influences residents' travel patterns (Lin et al., 2015), it is crucial to adjust the spatial distribution of different activity facilities based on the distribution and scale of various types of residents' daily activity centers. Additionally, optimizing the spatial distribution of public service facilities to align with the actual activity demands of residents is recommended. This is especially important for key nodes within UTNs. **Second,** decision-making and planning departments can make informed adjustments to the level of public transportation connectivity among different areas, taking into account the level of urban spatial interaction formed by various types of travel connections. The layout of public transportation facilities can be optimized according to the intensity of spatial interaction and travel demand. For example, for the regions with a high level of spatial interaction, bus/subway stations and routes can be appropriately increased or supplemented by other transportation options, such as shared bikes, e-scooters, and taxis. **Third**, based on the polycentric and sectoral structural characteristics of the different UTNs, authorities should prioritize the improvement of community public service facilities, transportation and municipal infrastructure, and urban safety facilities based on the specific needs of residents' daily activities and travels. This approach will enhance urban livability and service capacity, optimize the internal spatial layout of the city, and promote functional reorganization. For instance, owing to the significant disparity between the actual spatial functional zoning and the existing administrative boundaries, thoughtful adjustments to administrative divisions should be considered. These adjustments will help optimize the spatial organization structure, enhance urban governance level and development efficiency.

6. Conclusions

Urban structure is a crucial and complex concept that greatly influences the livability and sustainability of cities. In this Beijing-based study, the urban travel structure is comprehensively revealed from a multi-activity view. We first inferred the locations and types of daily activity for over four million urban residents by multi-source data fusion. Subsequently, we aggregated eight types of travel flows at the grid scale based on the diverse travel behaviors of millions of individuals, allowing us to construct eight UTNs. Through the integration of complex network analytics and spatial analysis methods, we examined the structural similarities and disparities across multiple dimensions. Our results reported that all UTNs in Beijing exhibit significant spatial heterogeneity, hierarchical, and dependency characteristics. More importantly, the spatial organization and interaction patterns of the UTNs show a polycentric hierarchical structure, while the distribution of communities aligns with a sector model. This indicates that the current urban structure of Beijing is a hybrid pattern, characterized by the coexistence of polycentric and sector patterns. Overall, our study provides valuable insights into the structure and functionality of urban systems, offering a new research perspective and empirical foundation for comprehensively depicting and measuring urban structure.

Inevitably, this study has some limitations. **First**, a major limitation of this study is the comparison metrics of UTNs. While we quantified the structural characteristics of each UTN across different dimensions, the examination of similarities and disparities between networks relied on qualitative analysis. In the subsequent study, it is crucial to enhance the analytical framework by incorporating state-of-the-art quantitative methods to measure the similarity and disparity of the various networks. **Second**, for simplicity, we did not consider the service hours of POIs when calculating the dominant activity category within activity locations. This oversight could potentially lead to including closed POIs in the calculation, which may not accurately represent the actual dominant activity category. The service hours of POIs should be considered in the activity identification framework in future studies to ensure a more accurate representation of the dominant activity category. **Third,** urban system is a network that encompasses multiple elements such as population flow, material flow, and information flow, this study solely focused on exploring the urban structure shaped by various travel flows. While acquiring different elemental flow data within cities can be challenging, it is crucial to pursue consistent multidisciplinary research and collaborative efforts to build a comprehensive urban network system. Such endeavors would provide more comprehensive and systematic scientific support for urban planning and the development of smart cities.

CRediT authorship contribution statement

Jian Liu: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Writing - original draft, Visualization, Writing - Review & Editing.

Bin Meng: Conceptualization, Methodology, Resources, Supervision, Writing- reviewing and editing, Funding acquisition.

Changsheng Shi: Software, Visualization.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2023.104634.

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