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Unveiling fine-scale urban third places for remote work using mobile phone big data

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ABSTRACT

Third places offer a creative alternative for both work from traditional office and home, which are becoming increasingly popular. Previous studies primarily focused on qualitative analyses and survey investigations, lacking quantitative studies exploring remote work in third places. In this study, we proposed a quantitative approach to identify and characterize the fine-scale third places for remote work, with the application in Beijing, China. Initially, we identified knowledge workers who were capable of remote work through mobile office app usage. Subsequently, we delineated the finer-scale distribution of third-place visits of remote workers using mobile phone signaling data and geospatial information. Finally, we utilized the eXtreme Gradient Boosting model and SHapley Additive exPlanations value to explore the association between third-place visits for remote work and the surrounding built environment. The results revealed that (1) approximately 61.43 % of total employees had the potential to work remotely, with 11.27 % opting for remote work in third places and 4.35 % choosing specific commercial third places; and (2) the popularity of these third places was characterized by high-density mixed-use surroundings, proximity to residential communities, and easy accessibility to subway stations. The findings can reinforce the establishment of urban design guidelines for third places, thereby contributing to the development of hybrid work models and sustainable cities.

1. Introduction

With the rapid development of information and communication technologies (ICT), remote work, also known as teleworking, telecommuting, working from home (WFH) and working from anywhere (WFA), is widespread in ICT- and knowledge-intensive industries, and high-skilled knowledge workers (Barrero et al., 2021). These knowledge workers are professionals who leverage their expertise, critical thinking, and interpersonal skills to generate value for organizations, encompassing computer programmers, scientists, design thinkers, lawyers, editors, academics, etc. (Drucker, 1959; Davenport, 2005). They have the capability to work remotely from any location due to their expertise in digital technology platforms (e.g., email, video conferencing, etc.) and embracing flexible work arrangements (Soga et al., 2022). According to estimates, 37 % of jobs can be performed entirely remotely in the United States, and approximately 20 % of the time can be spent working remotely in a long-run equilibrium (Bloom, 2020; Dingel & Neiman, 2020). More generally, the coronavirus disease 2019 (COVID-19) pandemic has also accelerated the transition away from traditional office work. In the post-pandemic era, the hybrid work model, integrating traditional office work with remote work, may become universal as some companies shift towards flexible work arrangements (Alexander et al., 2021; Mouratidis & Papagiannakis, 2021; Šmite et al., 2023). By 2023, the number of remote workers in China had reached 507 million, coexisting with diverse work models, including work from office, home, and other flexible options (China Internet Network Information Center, 2023; Bloom et al., 2015).

Third place, as a type of informal public gathering place outside of the home and workplace (Oldenburg, 1989), is becoming increasingly popular. Characterized by functionality, accessibility, comfort, and sociability, third places mainly include community centers, shopping centers, libraries, gyms, and outdoor recreational activity venues. As many companies move towards a hybrid work model, the popularity of third places for remote work is on the rise. These places provide a creative alternative to working both from the traditional office and home, presenting new opportunities for profit by offering facilities for remote

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work (Fig. 1). The categories of third places for remote work mainly include cafés, teahouses, bookstores, libraries, study rooms, fast-food shops, community centers, and coworking spaces (Brown, 2017; Rosenbaum, 2006). Within these third places, employees commonly undertake tasks such as focused work, idea generation, client meetings, administrative duties, and casual phone conversations. Moreover, some studies have shown that about one-third to one-half of remote workers spend some of their work hours in third places, with approximately 10% stating that third places such as cafés are their preferred work locations (Gaskell, 2023; Lund et al., 2020).

Remote work in third places is widely recognized as beneficial for both employees and employers. It provides a valuable opportunity to reduce commuting distances and associated environmental impacts, thereby contributing to the development of sustainable cities (Shakibaei et al., 2021; Sweet & Scott, 2022; Inkinen et al., 2020). Compared with working from home, working from third places can overcome various drawbacks, including distractions from household chores, unstable network infrastructure, inadequate office space, increased household energy consumption, and the perception of loneliness (Buffer, 2020; Cuerdo-Vilches et al., 2021; Ku et al., 2022). Compared with working from the traditional office, remote workers prefer third places closer to their homes to avoid long commuting distances (Nelson et al., 2007), thus offering an opportunity to adopt green transportation modes, alleviate traffic congestion, and mitigate associated energy consumption and carbon emissions (Hopkins & McKay, 2019; Li et al., 2023). Remote work in third places can lead to reduction of office operation, improvement of productivity due to flexible extended work hours (Atkyns et al., 2002; Grawitch et al., 2010), mitigation of exposure to illness or adverse weather conditions, and the achievement of a healthier work-life balance (O'Brien & Aliabadi, 2020), thus resulting in reduced turnover and absenteeism (Yang et al., 2022).

Furthermore, scholars have explored worker types, work efficiency, the built environment, influencing factors in third places, as well as their space-time geography. A study has indicated that young and highly educated knowledge workers are more inclined to work in third places utilizing semi-structured interviews and case studies. This inclination is influenced by factors such as ambiance, facilities, location, and the desire to avoid home or office (Poelsema, 2020). Some studies, utilizing focus groups, interviews, and survey questionnaires, have explored the impact of physical and psychological factors in third places on work engagement and creativity enhancement, suggesting opportunities to transform inefficient spaces into flexible third places (Monhollen, 2022; Nagayama, 2023). Di Marino and Lapintie (2017) identified several spatial characteristics, such as pedestrian-oriented design, accessibility by public transportation, proximity to attractive public places (e.g., parks, gardens, squares), and the integration of other functions, to enhance the attractiveness of third places for remote work through field investigations and spatial analysis. The prevalence of third-place remote work may also depend on the ubiquity of online activities and complex factors related to urban form, spatial planning, decision systems, and societal perceptions of future cities (Mouratidis & Papagiannakis, 2021). Regions having third places for remote work and social interactions are recognized as having a high community quality of life.

Therefore, identifying and characterizing the fine-scale urban third places for remote work holds significant importance. Relatively less attention has been given to the phenomenon and spatial distribution of remote work in third places such as cafés and libraries, compared with spatial analysis of traditional workplaces (Armstrong et al., 2021) and emerging workplaces, such as home offices (Bick et al., 2020) and innovative parks (Clare, 2013; Pancholi et al., 2019). Methodologically, previous studies primarily adopted qualitative analysis, including interviews, field investigations, case studies, etc., to analyze the advantages and disadvantages of remote work, as well as the mechanisms of working from the office, home, and hybrid locations (Felstead & Henseke, 2017; Voll et al., 2023). Among the limited quantitative studies, the majority employ surveys, diaries, or focus groups to explore the frequency and spatial preferences of third place for remote work (Brown, 2017; Waxman, 2006). These methods, based on questionnaire surveys and activity logs, enable the precise capture of the spatiotemporal behaviors of remote workers in third places, especially in large-scale, long-term national surveys. However, limitations such as small sample sizes and unclear survey questions may lead to inaccurate results, and the significant human resources required for data collection present additional challenges, hindering a comprehensive analysis of the widespread spatial distribution (Andrey et al., 2004). With the advancement of mobile phone technology and the widespread use of mobile apps, mobile phone big data are extensively utilized to assess job-housing balance, workplace segregation, and commuting patterns (Pajević & Shearmur, 2017; Liu et al., 2020; Wang et al., 2022; Zhou et al., 2021). The usage of mobile apps and mobile phone signaling data offers the potential for large-scale identification of third-place locations (Choujaa & Dulay, 2009). However, it is worth noting that this data typically remains constrained to kilometer grid scales, lacking identification of the spatial distribution of third-place visits by remote workers at a finer scale. Meanwhile, cutting-edge machine learning models offer an efficient solution for further exploring the visiting preferences and spatial characteristics of third places for remote work, due to their robust and flexible algorithmic architecture (Wang & Biljecki, 2022).

In summary, existing studies have overlooked the emerging phenomenon of remote work in third places, lacking large-scale quantitative analysis based on new data and models, as well as fine-scale spatial distribution and characteristics exploration. Addressing these gaps, this study primarily solves three challenges: (1) identifying knowledge workers who are capable of remote work, (2) delineating the

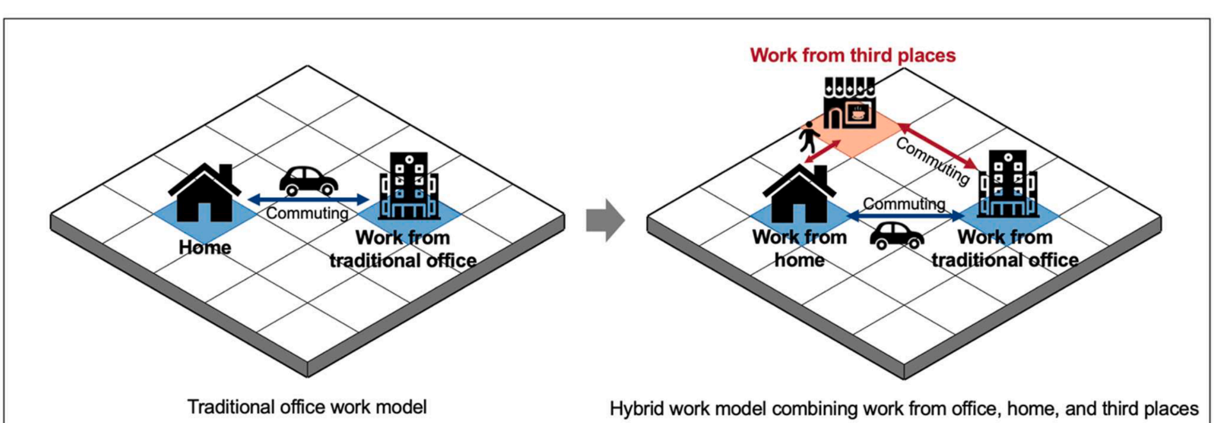


Fig. 1. The transition from traditional office work to remote work in third places.

distribution of third-place visits by remote workers at the fine scale, and (3) exploring the association between third-place visiting preference and surrounding built environment. To tackle these challenges, the study proposed a quantitative approach to efficiently identify and characterize the fine-scale urban third places for remote work through mobile phone big data and machine learning models, with the application in Beijing, China. The findings of this study can provide valuable insights for urban planners and designers in establishing urban design guidelines for third places, thereby contributing to the development of hybrid work models and sustainable cities.

2. Methodology

2.1. An approach to identify and characterize third places for remote work

To quantitatively unveil the fine-scale urban third places for remote work, a four-step systematic approach is proposed (Fig. 2). Firstly, knowledge workers who are capable of remote work are identified by selecting employees using mobile office apps. Secondly, potential third places for remote work are identified by selecting the locations where these knowledge workers have the longest duration of stay during working hours on weekdays using mobile phone signaling data, while excluding their residential and office locations. Thirdly, the building-scale distribution of third-place visits for remote work is delineated after excluding locations lacking third places, supplemented with field investigations to further observe the indoor environment. Finally, the association between third-place visits of remote workers and the surrounding built environment is explored using the eXtreme Gradient Boosting (XGBoost) machine learning model and SHapley Additive exPlanations (SHAP) value analysis. The XGBoost model, a relatively recent technique initially proposed by Chen and Guestrin (2016)), has the ability to handle complex high-dimensional relationships. It also exhibits remarkable performance and rapid processing speeds, making it the preferred choice for our regression analysis (Parsa et al., 2020; Mousa et al., 2019) (see Section 3 in Supplementary materials). Additionally, the SHAP value was adopted to provide various interpretations based on the contribution of each input variable in the model system (Lundberg & Lee, 2017).

2.2. Materials

2.2.1. Study area

Beijing, the capital of China, is well-known for its excellent network infrastructure, thriving innovative industries, and large workforce (Fig. 3). Beijing has 11.58 million employees, a large proportion (i.e., 81 % of the overall industry) of the tertiary industry, with the substantial growth of the digital economy, high-tech industry, and strategic emerging industries (Beijing Statistical Yearbook Committee, 2022). In recent years, Beijing has introduced policies to encourage remote work. For instance, the “2022 Beijing Comprehensive Traffic Management Action Plan” (Beijing Municipal Commission of Transport, 2022) has implemented strategies to promote remote work for sustainable development. Currently, many innovative companies in Beijing have adopted hybrid work models. Therefore, understanding the shifts in employees’ lifestyles and identifying third places for remote work in Beijing hold significant research implications and representativeness for the development of future work models and new workplaces.

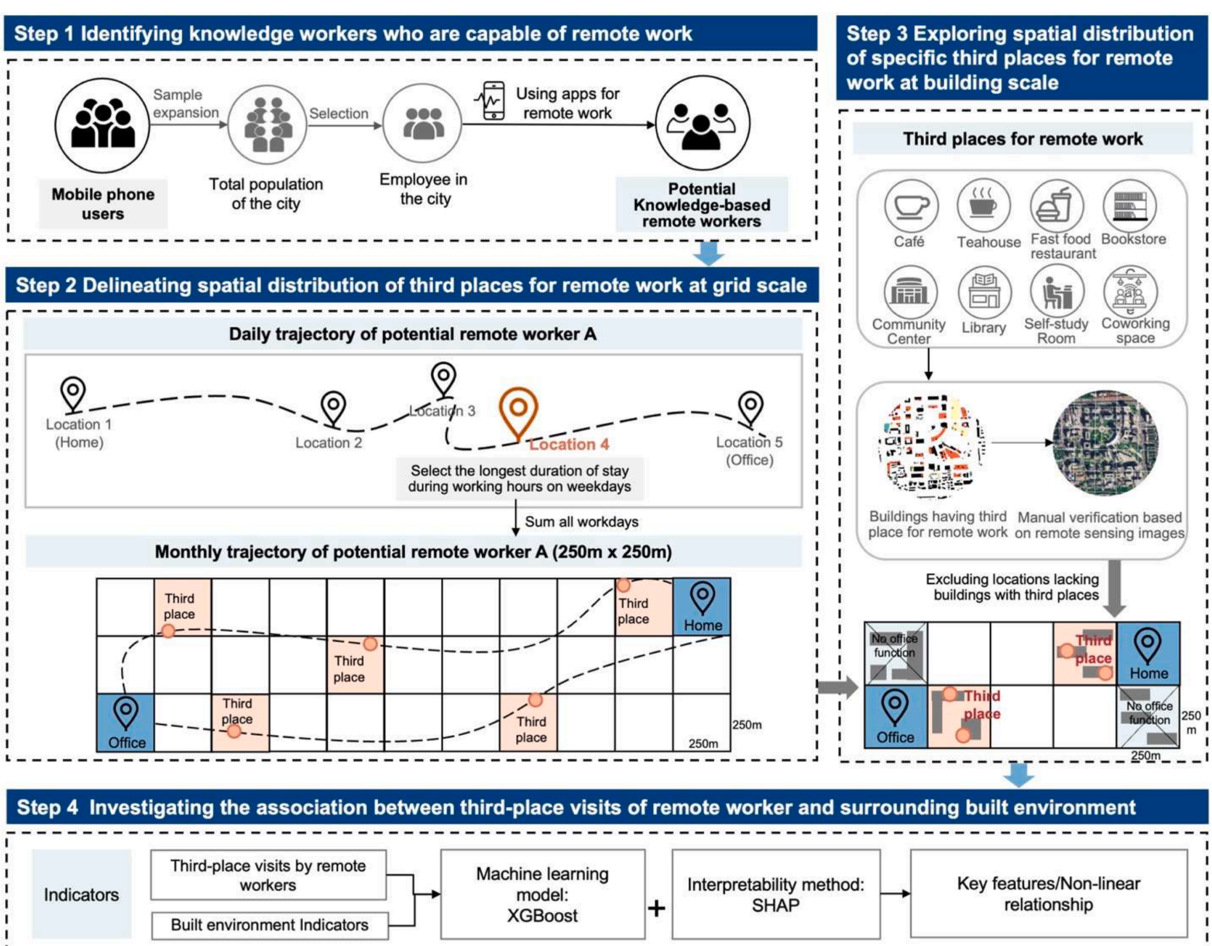


Fig. 2. Four-step approach for identifying and characterizing third places for remote work.

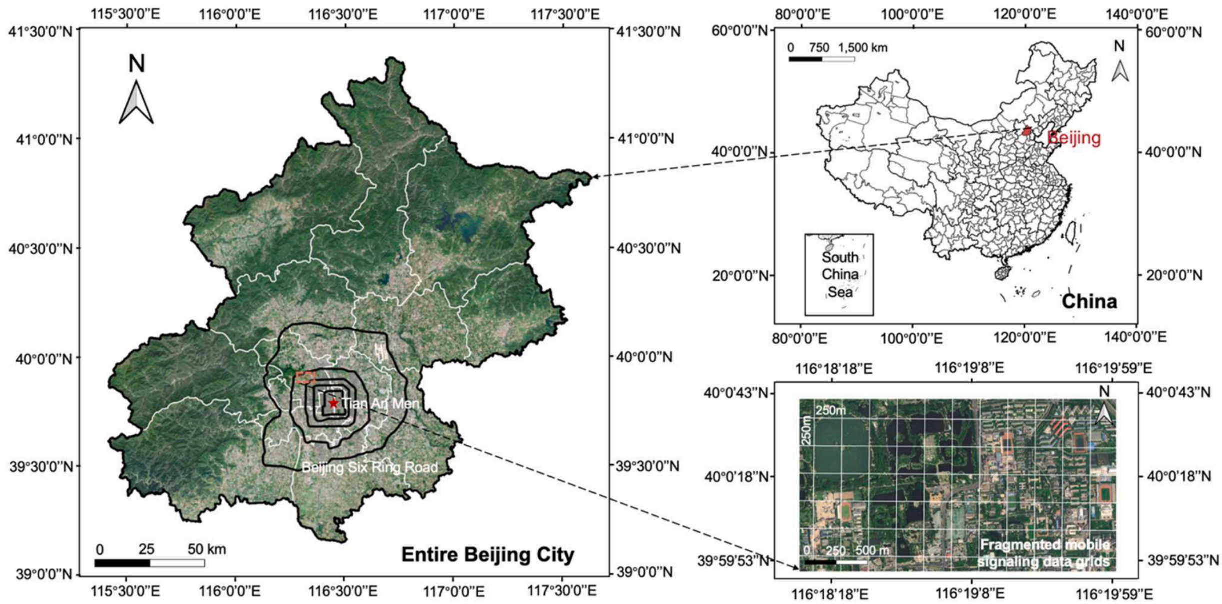


Fig. 3. Study area.

2.2.2. Data source

(1) **Mobile phone big data.** Encompassing mobile phone signaling data and monthly total mobile app usage, the data utilized were acquired from China Unicom in July 2022, which held a significant share of the mobile service market in Beijing (Xu, 2020). After a series of preprocessing operations on the original mobile phone big data by China Unicom, user positions from the original cellular towers were allocated to regular spatial grids (250 $m \times$ 250 m) and anonymized data was provided through a data query platform (http://daas.smartsteps.com/) (see Section 1 in Supplementary materials). We employed structured query language (SQL) to process data from platform, excluded users who spent fewer than 10 days in the city within a month, and aggregated the data into spatial grids. The data consist of 102,000 spatial grids, covering 10.47 million population throughout the duration of July 1st to 31st, 2022 (00:00:00–23:59:59). The attributes of each record include the user identification (UID), basic user information (e.g., age and gender), app usage details (e.g., app names and monthly total usage time), timestamp (start and end time) for each event, grid numbers of the starting and ending positions for each trip, and event types (e.g., home, workplace, and visiting places) (Table 1). A recorded stay is defined as where a user remains at the same location for over 30 min. The event types for a user are inferred by China Unicom through a long period of observations of the users' stay in each grid during work hours and night. To protect user privacy, all data are anonymized, and the export of individual information, such as UID, is strictly prohibited. It is important to note that permissions are secured with restrictions solely for academic research.

(2) **Geospatial data.** The utilized geospatial data comprised point of interest (POI), area of interest (AOI), building footprint, road network, high-resolution remote sensing images, and indoor photos shared by consumers on the Dazhong Dianping platform (Table 2). The POI, AOI, building footprint, and road network data were collected from digital navigation maps in China, providing valuable information to investigate the relationship between third-place visits for remote work and the surrounding built environment. In detail, the POI data encompassed extensive attributes, including names, categories, and coordinates (i.e., longitude and latitude), enabling the identification of third places (e.g., cafés, libraries etc.), transportation stations (e.g., subway and bus stations), and other significant places (e.g., office buildings). The AOI data represented the polygon version of POI, delineating the boundaries of land use, such as schools, residential communities, green spaces, and industrial parks. The road network data only included urban road centerlines, without internal paths in communities. Building footprint data and remote sensing imagery were employed to identify buildings and underwent manual verification. Additionally, consumer-shared photos were utilized to visualize the indoor environment of popular third places.

Table 1
Examples of mobile phone big data.

UID	620**000	777**594	834**000	922**592
Age	19–24	30–34	45–49	50–54
Gender	Female	Male	Female	Male
App name	Gmail	WPS Office	Tencent Meeting	MaiMai
App usage time (hour per month)	10,560	1594,221	7772	3040
Start time	10:16:39	18:32:26	7:56:55	1:34:47
End time	11:34:13	22:26:11	18:38:22	9:43:51
Grid number of starting position	100**390	255**500	700**060	300**410
Grid number of ending position	300**320	255**600	100**000	100**390
The event type of the starting position	Visiting place	Workplace	Home	Workplace
The event type of the ending position	Visiting place	Visiting place	Workplace	Home
Date	20,220,701	20,220,715	20,220,721	20,220,731

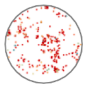
Note: ** Represents hidden numbers.

2.3. Methods

2.3.1. Identifying knowledge workers who are capable of remote work

We identified knowledge workers who were capable of remote work by specifically selecting employees using mobile office apps. Initially, we prioritized mobile office apps with high usage and features such as

Table 2
Description of geospatial data used in this study.

Diagram	Data type	Data description	Data source
	**POI**	Point data with names, categories, and coordinates	Amap, 2022. (https://www.amap.com/)
	**AOI**	Polygon data with boundaries, names, categories, and coordinates	Baidu Map, 2022. (https://map.baidu.com/)
	**Building footprint**	Building footprint with layer information	Baidu Map, 2018; OpenStreetMap, 2022. (https://www.openstreetmap.org/)
	**Road network**	Urban roads excluding internal paths in communities	Amap, 2019. (https://www.amap.com/)
	**Remote sensing image**	High-resolution remote sensing imagery of 2m resolution	Google Map Imagery, 2022. (https://earth.google.com/)
	**Consumer-shared photo**	Information containing indoor photos shared by consumers	Dazhong Dianping platform, 2023. (https://account.dianping.com)

Note: All geospatial data were converted to the WGS84 coordinate system.

remote file delivery, online conference communication, online business networking, and remote office tools. Since the usage time is heavily concentrated on a few apps, we sorted the top 1130 most used apps from more than 17,000 apps to carry out classification, after which, 33 mobile office apps were selected (Table 3). Then, we identified employees using mobile phone signaling data by selecting users who had spent more than 10 days in Beijing during a single month, identified with a workplace, and fell within the age range of 19–59. To ensure the representativeness of the data from China Unicom, the number of users was expanded to the entire population of Beijing using weights, which were calculated by dividing the population data obtained from the statistical bureau by the number of China Unicom users in each district. Subsequently, we successfully identified employees in Beijing who used these selected mobile office apps, suggesting their potential as knowledge workers with the ability to work remotely.

Table 3
Selected mobile office apps.

Categories	Names	Number	Total usage time (hours per month)
Remote file delivery	Ding Talk, BITTORRENT, QQmail, Baidu Netdisk, 360 Public Resources, Cloud Hub, eDonkey, MicroCloud, Wo Mail, 139 Mail, 263 Mail, Gmail, Jinshan Public Resource, 189 Mail, WAP Unified Portal, QQPim, TELNET, NetEase Mail, TRI, Sina Mail, Ali Mail	21	14,000,000
Online conference communication	Enterprise WeChat, Skype, Tencent Meeting	3	1180,000
Online business networking	CamCard, Yongyou IUAP, MaiMai	3	39,000
Remote office tool	WPS Office, Baidu Library, CSDN, Haochen CAD, CamScanner, Outlook	6	1660,000
Total		**33**	16,900,000

2.3.2. Delineating the spatial distribution of third places for remote work at grid scale

To identify potential third-place visits for remote work, we initially obtained all daily stay locations of the selected knowledge workers using mobile phone signaling data. Then, we specifically selected the locations with the longest stay duration for each weekday falling within the time range of 7:00–20:00, excluding their residential and office locations. The time range was chosen as it corresponded to the prevailing working hours observed among the Beijing population. The home location was determined based on where the user mostly stayed during the night for 30 consecutive days. The workplace location was identified as the place where the user predominantly had the longest stay during working hours on weekdays throughout the month. If the user visited locations other than their home or workplace, these places were categorized as third places. In total, there were 21 weekdays in July 2022. By aggregating chosen daily longest stay locations, we obtained the potential third-place visits for remote work among these knowledge workers in spatial grids of 250 × 250 meters in July. The visualization maps were generated using QGIS Version 3.22 (https://qgis.org/).

2.3.3. Exploring the spatial distribution of specific third places for remote work at building scale

After excluding grids lacking necessary third places, we conducted a more detailed analysis to obtain a building-scale distribution of specific third-place visits by remote workers. It was worth noting that we focused on typical profit-generating types of third places from an urban perspective. Third places such as squares, parks, friends' homes, or others' workplaces, which were challenging to precisely delineate, were excluded from our consideration. In total, we identified 9043 specific third places within Beijing, classified into 8 main types, including 3310 cafés, 1940 teahouses, 1274 bookstores, 878 fast-food shops, 695 community centers, 586 libraries, 317 study rooms, and 43 co-working-spaces. We employed building footprint and specific third-place POI data to identify buildings with third places and used remote sensing images to manually supplement missing or anomalous buildings. Then, we exclusively chose grids that had remote workers' visits as well as third places and evenly distributed the monthly visits based on the number of third places in each grid. Following that, we aggregated the number of visits by remote workers across various third places within the same building. As shown in Eq. (1), let P_i represent the number of monthly visits to third places by remote workers in building i, which is calculated as follows:

$$P_i = \sum_{i=1}^{n_i} \left(P_k \middle/ \sum_{j=1}^{n_j} N_{jk} \right) \tag{1}$$

where P_k represents the number of monthly visits to third places by remote workers in grid k. N_{jk} represents the number of third places of type j in grid k. n_i is the number of third places in building i, and n_j is the number of third place types. After calculation, we successfully obtained the building-scale spatial distribution of specific third places for remote work (Fig. 4). Combining photos shared by remote workers and field investigations, we further observed the indoor environment of these third places.

2.3.4. Investigating the association between third-place visits of remote workers and the surrounding built environment

To further investigate the relationship between third-place visits of remote workers and the surrounding built environment, we selected 15 indicators based on the "5Ds" classification framework (Table 4) (Ewing & Cervero, 2010). The dependent variable is the number of third-place visits of remote workers in a building within a month. The independent variables encompass design, density, diversity, distance to transit and destination accessibility. Specifically, for the design indicator, we calculated the number of third places in the building. For density and diversity, we considered indicators such as the floor area ratio, building

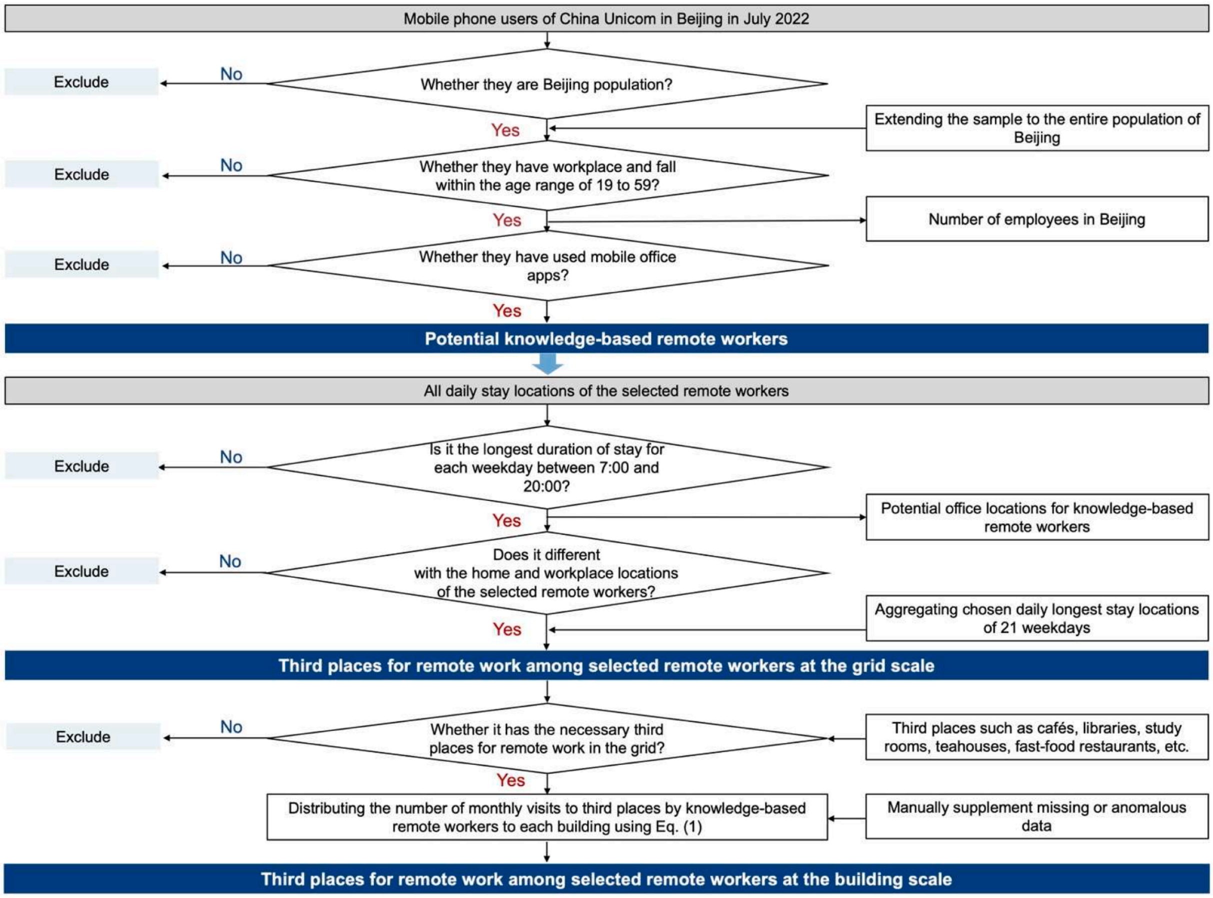


Fig. 4. The framework of identifying third places for remote work.

Table 4
Description of dependent and independent variables (n = 5418).

Indicator	Description	Data	Unit	Mean	Standard Deviation
Dependent variable					
Number of third-place visits	Monthly visits of remote workers in third places of each building	Mobile phone signaling data, POI, building footprint	#	1810	3028
Independent variable					
Design					
Number of third places	Number of third places in the building	POI, building footprint	#	1.40	1.10
Density					
Floor area ratio	Block floor area ratio comprising the building	building footprint	—	1.40	0.96
Building coverage ratio	Block building coverage ratio comprising the building	building footprint	—	0.23	0.11
Diversity					
Density of POIs	The total number of POIs in the block comprising the building	POI, building footprint	$\#/m^2$	0.002	0.002
Functional mixture	Block functional mixture comprising the building	POI, building footprint	—	2.10	0.24
Distance to transit					
Distance to external transportation	Distance of the building to the nearest external transportation (i.e., airport, railway station, intercity bus terminal)	AOI, building footprint	km	2.37	1.39
Distance to the subway station	Distance of the building to the nearest subway station	POI, building footprint	km	0.63	0.67
Distance to the bus station	Distance of the building to the nearest bus station	POI, building footprint	km	0.16	0.12
Normalized angular integration	Nearest road's normalized angular integration by space syntax tool	Road network	—	0.79	0.12
Normalized angular choice	Nearest road's normalized angular choice by space syntax tool	Road network	—	0.97	0.21
Destination accessibility					
Distance to school	Distance of the building to the nearest school	AOI, building footprint	km	0.21	0.23
Distance to residence	Distance of the building to the nearest residential communities	AOI, building footprint	km	0.05	0.10
Distance to green space	Distance of the building to the nearest green space or parks	AOI, building footprint	km	0.54	0.50
Distance to industry	Distance of the building to the nearest industrial park	AOI, building footprint	km	0.74	0.46
Distance to office	Distance of the building to the nearest office building	POI, building footprint	km	0.12	0.13

Note: # represents the count. Given that the vast majority of third places are situated within Sixth Ring Road, the calculation of indicators within this area is considered representative. More details are shown in Section 2 in Supplementary materials.

coverage ratio, density of POIs, and functional mixture (Chen et al., 2023; Wu et al., 2022). To assess the distance to transit, we determined the distance from each building to the nearest transportation hubs such as airports, railway stations, subway stations, and bus stations (Zhao, 2013) and employed normalized angular integration and normalized angular choice using space syntax tools (Hillier et al., 2012). Additionally, we measured the distance from each building to its closest schools, residential communities, green spaces, industrial parks, and office buildings, as indications of destination accessibility (Hostettler Macias et al., 2022; Rahman et al., 2023).

Subsequently, we compared multiple linear regression (MLR) models with several machine learning (ML) models known for handling multivariate non-linear relationships, such as Decision Tree (DT) (Ding et al., 2019), Random Forest (RF) (Hatami et al., 2023), Multilayer Perceptron Regressor (MLP Regressor) (Ghunimat et al., 2023), and eXtreme Gradient Boosting (XGBoost) (Parsa et al., 2020; Spadon et al., 2019) (see Section 3 in Supplementary materials). We used metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), R-Square (R^2), and adjusted R-Square (Adjusted R^2) to compare their performance. Smaller values of MAE, MSE, and RMSE indicate better model performance, while higher R^2 and Adjusted R^2 imply superior model performance (Zhou et al., 2022). In this study, we utilized Python 3.10 to systematically conduct the modeling process.

The compared results between MLR models with several ML models showed overall better performance of non-linear models than linear models, suggesting the presence of multivariate non-linear relationships between third-place visits and built environmental variables. For all the non-linear models, the XGBoost model exhibited the highest R^2 and Adjusted R^2 and the lowest MAE, MSE, and RMSE, consistent with previous studies demonstrating its superior performance compared to other machine learning models (Schlögl et al., 2019; Jabeur et al., 2021). Additionally, the XGBoost model boasts high accuracy and rapid processing, with lower computational costs and complexity (Chen & Guestrin, 2016; Mousa et al., 2019). Combined with SHAP value analysis, the model not only estimates feature importance, feature dependence plots, local interpretation, and summary plots, but also captures the positive or negative impact of each feature within every individual sample, thereby enhancing the interpretability of machine learning (Lundberg & Lee, 2017; Parsa et al., 2020; Guo et al., 2023). Therefore, we employed the XGBoost model and SHAP values to explore the non-linear relationship between dependent and independent variables in this study.

3. Result

3.1. Identification of potential remote workers and mobile office app usage

The usage condition of selected 33 mobile office apps is illustrated in Fig. 5. Among them, DingTalk, Skype, Yonyou IUAP, and WPS Office have the longest usage time for remote file delivery, conference communication, business networking, and office tools, respectively. Additionally, DingTalk, Enterprise WeChat, and QQ Mail stand out with the highest user engagement, collectively accounting for nearly half of the total users of mobile office apps. DingTalk exhibits the highest usage intensity, boasting the longest monthly usage time and the largest user base among all mobile office apps. Moreover, the average usage time of mobile office apps of employees in a month is 1.43 h.

Upon extending mobile phone users to the entire population of Beijing, a total of 21.82 million population and 11.81 million employees were identified, covering approximately 101,000 grids and 91,200 grids, respectively. Notably, a significant portion of 7.26 million were identified as potential knowledge workers capable of remote work, who used mobile office apps within these employees, covering approximately 80,500 grids. Among the identified potential remote workers, there is a slightly higher representation of males (52.75 %) compared to females

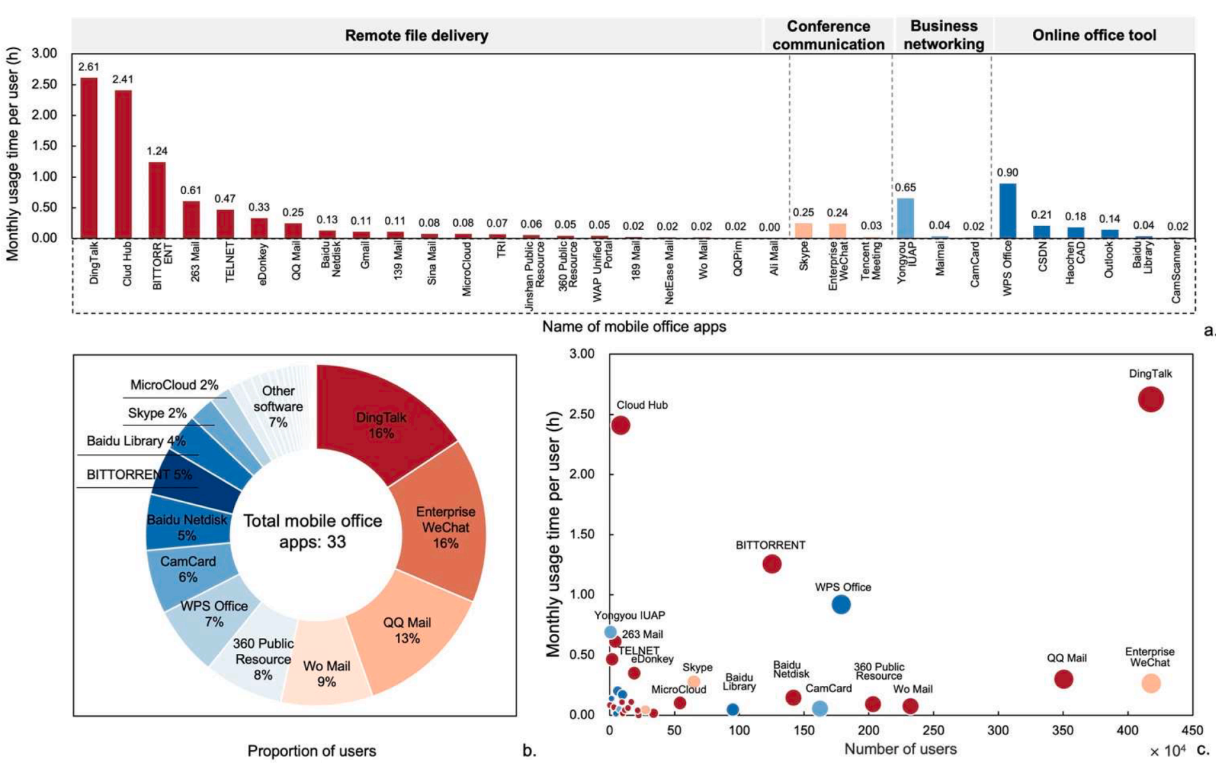


Fig. 5. Usage condition of 33 mobile office apps.
(*a*) Monthly usage time per user of different mobile office apps. (*b*) The proportion of users of different mobile office apps. (*c*) Usage intensity of different mobile office apps.
Note: Some users may utilize more than one app, leading to potential duplicate counts.

(47.25 %). In four 10-year intervals from 19 to 59, the majority of remote workers fall within the 30 to 39 age group (see Table S3 in Section 4.1 of the Supplementary materials). In summary, 61.43 % of total employees have the potential to work remotely, with high-intensity mobile office app usage, indicating Beijing's substantial suitability for adopting hybrid work models.

3.2. Grid-scale spatial distribution of third places for remote work

We identified potential third-place visits for remote work among selected knowledge workers. An average of 1.33 million employees were identified as engaging in remote work from third places, distributed across approximately 42,700 grids. They spent an average of 3.99 h per day at these third places. As shown in Fig. 6a-c, upon aggregating daily visits of 21 weekdays (see Table S4 in Section 4.1 of the Supplementary materials), the monthly third-place visits by remote workers were distributed across urban (66.33 %), suburban (28.97 %), and exurban areas (4.70 %). The highest visits were observed in the Chaoyang and Haidian Districts, between the Fifth and the Sixth Ring Roads. Additionally, there is minimal variation observed across different weekdays. In summary, 11.27 % of total employees had long-duration stays in third places during working hours on weekdays, thereby earning recognition as third-place remote workers in this study.

Concerning the spatial distribution at the grid scale, we observed

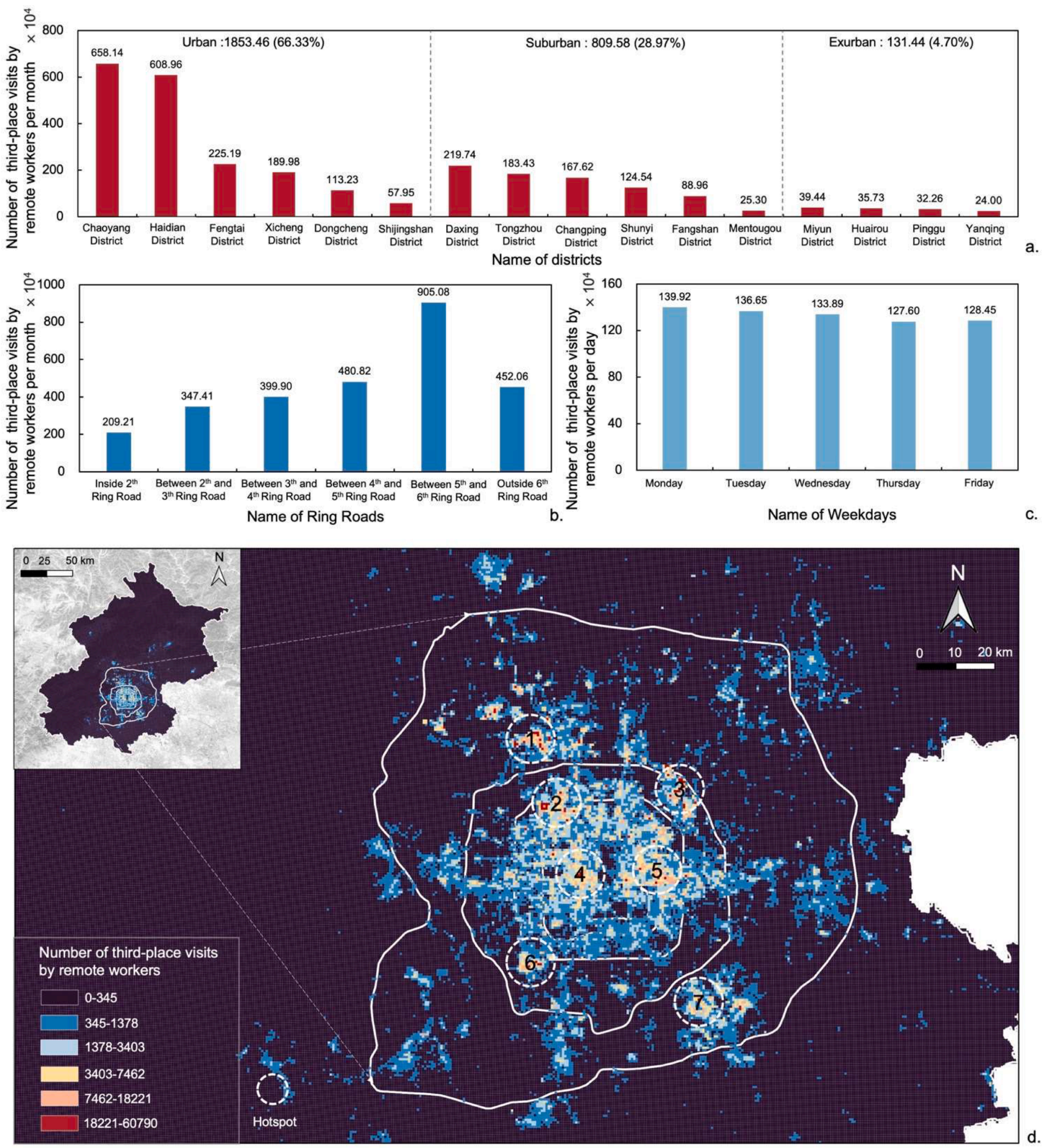


Fig. 6. Spatial distribution and statistics of third-place visits by remote workers.
(*a*) Monthly third-place visits of remote workers by district. (*b*) Monthly third-place visits of remote workers by ring road. (*c*) Third-place visits of remote workers by weekday. (*d*) Spatial distribution and hotspots of third-place visits of remote workers.
Note: 1. Shangdi, 2. Zhongguancun, 3. Wangjing, 4. Financial Street, 5. Central Business District, 6. Fengtai Science Park, 7. Yizhuang.

that third-place visits by remote workers were concentrated in seven hotspot areas, that is Shangdi, Zhongguancun, Wangjing, Financial Street, Central Business District, Fengtai Science Park, and Yizhuang (Fig. 6d). In terms of geographical aggregation, the third-place visits by remote workers were primarily clustered within innovation industry agglomeration zones. This could be attributed to the abundance of third-place offerings and a concentration of knowledge workers in these zones, often associated with professional, managerial, and executive occupations. These occupations may have flexible work arrangements and a high prevalence of remote work.

3.3. Building-scale spatial distribution of specific third places for remote work

Using Eq. (1), we distributed the monthly third-place visits by remote workers in each building, excluding grids lacking necessary third places. There were an average of 0.52 million remote workers identified engaging in specific commercial third places, distributing across 6490 buildings and 4680 grids. As depicted in Fig. 7, a majority of these buildings were equipped with café, teahouses, or bookstore-function third places, which also recorded the highest number of visits by remote workers. There were also 741 buildings featuring multifunctional third places. While the count of community centers was relatively high, the visits by remote workers there were comparably lower. Coworking spaces exhibited the lowest count, resulting in a relatively lower number of remote work visits. Additionally, one building housed 1.37 third places on average, with a range spanning from 1 to 25. The average remote workers' visits at each building amounted to 79, with a median of 35 per day. In summary, 4.36 % of the total employees were identified as working remotely in specific commercial third places.

As shown in Fig. 8, we selected buildings with higher visits within hotspots to delve into the indoor environment of popular third places through consumer-shared photos and field investigation. Notably, these selected buildings typically hosted multiple multifunctional third places, adjacent to innovative companies, traditional office spaces, and residential areas. We conducted random visits to 22 third places within these buildings, including Starbucks, Tims and KFC. A common thread of these third places was the provision of a conducive work environment. This encompassed aspects like adequate illumination, well-furnished interiors including tables, chairs, and sofas, as well as essential amenities such as reliable Wi-Fi connections and sufficient plug sockets for computer use. Additionally, these places offered an array of sustenance options such as coffee, snacks, and water, thereby generating profits through offering remote work services. Observing popular third places allows us to generalize attractive features, thereby assisting in the spatial design of third places.

3.4. Association between third-place visiting preference for remote work and surrounding built environment

Employing the optimal hyperparameters, the XGBoost model exhibited its peak performance as follows: MAE at 0.51, MSE at 0.44, RMSE at 0.67, R^2 and Adjusted R^2 at 0.73. Fig. 9 presented the summary plot and representative feature dependence plots using SHAP values, arranging features based on their importance in influencing third-place visits. The results revealed that the popularity of these third places was predominantly influenced by built environment attributes, manifesting differently under varying conditions. The top five influential factors, in descending order, are the floor area ratio, the number of third places, the distance from residential communities, the distance from subway stations, and the density of POIs (Fig. 9a). Concerning density, diversity, and design, the floor area ratio and the density of POIs exert more positive effects, and the number of third places has higher positive importance, implying that remote workers prefer to visit buildings housing multiple third places within mixed-use, high-density areas. Regarding destination accessibility, the distance to residential communities exists more negative relationships, suggesting a preference for third places close to their residences. While some prioritize proximity to traditional workplaces like office buildings and industry parks, it is less important. Concerning transit distance, the accessibility to subway stations of third places is more appealing to remote workers, compared with bus stations and road network accessibility. These complicated results might be better understood with the feature dependency analysis (Fig. 9b). The results indicate that there are more third-place visits for remote work when either the floor area ratio or the number of third places is above 1. The results also reveal that when the third place is located further away from residential communities (more than 200 m) and subway stations (more than 1 km), the proximity to residential

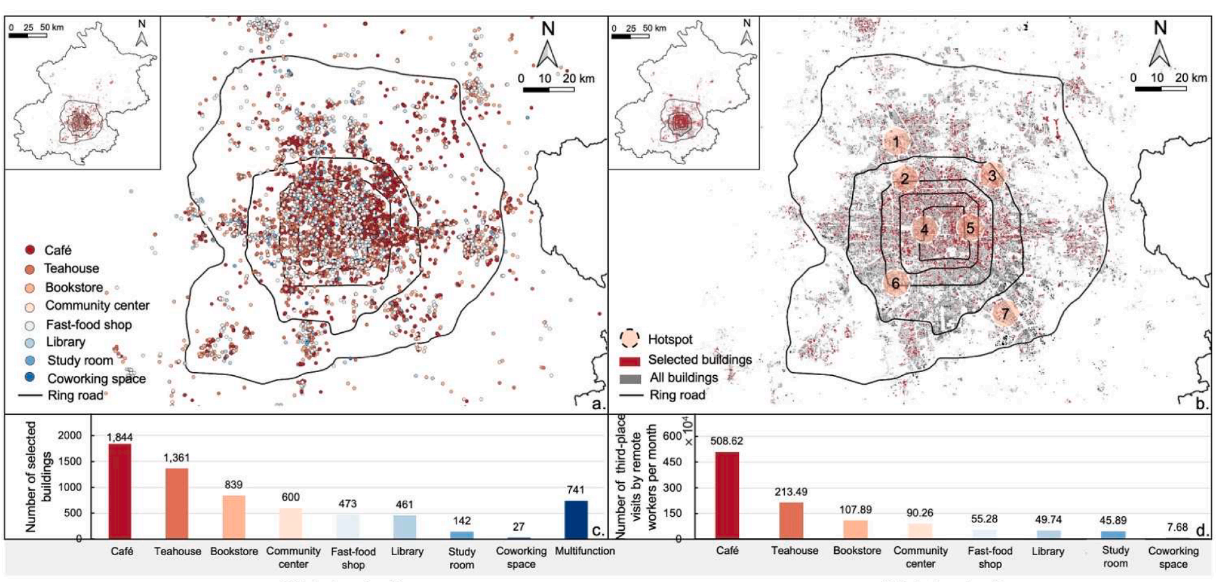


Fig. 7. Spatial distribution and statistics of specific third places for remote work.
(*a*) Spatial distribution of different third places. (*b*) Spatial distribution of selected buildings with both visits by remote workers and third places. (*c*) The number of buildings with different third-place functions. (*d*) Number of remote workers' visits within different third place types in July.
Note: 1. Shangdi, 2. Zhongguancun, 3. Wangjing, 4. Financial Street, 5. Central Business District, 6. Fengtai Science Park, 7. Yizhuang.

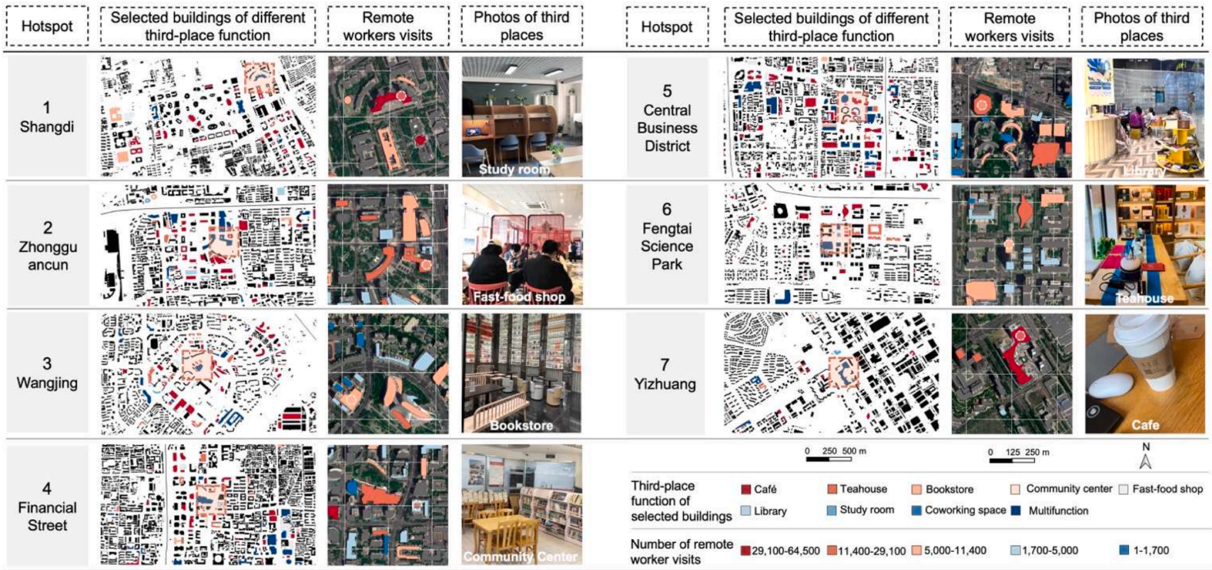


Fig. 8. Representative buildings and third places.

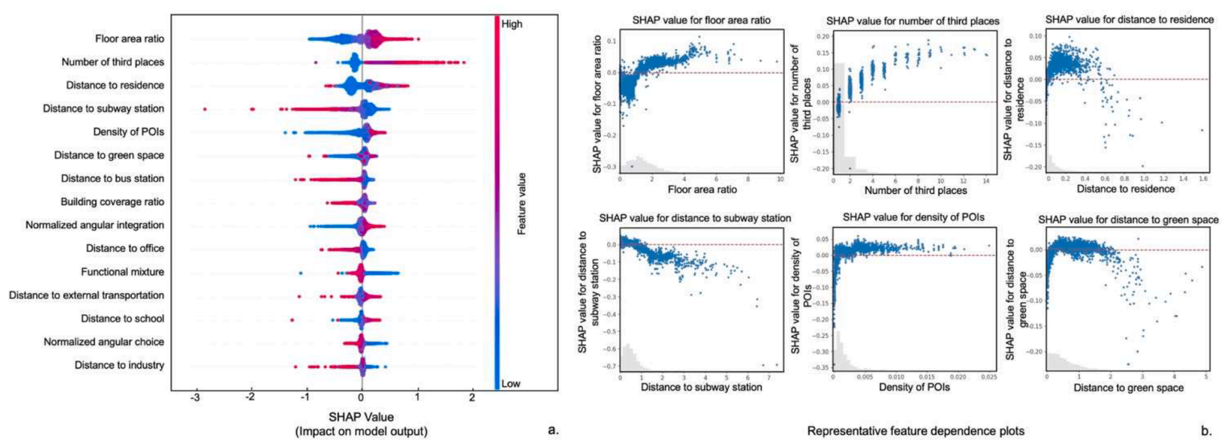


Fig. 9. Summary plot and feature dependency analysis.
(*a*) Summary plot by SHAP value. (*b*) Representative feature dependence plots.

communities and subway stations becomes more crucial. Overall, remote workers exhibit a preference for third places characterized by high-density mixed-use surroundings, proximity to residential communities, and convenient access to subway stations, among other built environment attributes (see Section 4.2 in Supplementary materials). These non-linear relationships offer a new perspective for understanding the third-place visiting preference for remote work.

4. Discussion

4.1. Academic contributions

To our understanding, this study represents one of the early endeavors utilizing mobile phone big data and machine learning models to autonomously identify and characterize the fine-scale distribution of third places for remote work. This study addresses the aforementioned challenges and offers multifaceted strengths. Firstly, our focus lies in comprehending the distribution of knowledge workers engaged in remote work within urban third places such as cafés and libraries, which has received less attention in previous studies. Secondly, our study introduces a quantitative approach to automatically identify and characterize the fine-scale distribution of third places for remote work. This process offers a larger scale and faster results compared to conventional survey-based methods (Dahik et al., 2020). We are among the pioneers in utilizing mobile office app usage and location data to identify third-place visits for remote work among knowledge workers. Thirdly, we conduct a detailed exploration of finer spatial distributions at multiple scales, from grid level to building level to indoor level, focusing on specific third places commonly chosen by remote workers. This level of detail surpasses previous endeavors that rely solely on mobile phone signaling data within kilometer grids (Zhou et al., 2018). Lastly, we employ the XGBoost machine learning model, along with SHAP values, to investigate the association between third-place preference for remote work and the surrounding built environment.

The conducted case study in Beijing underscores the feasibility of this approach, revealing that around 61.43 % of the total employees hold the potential for remote work, with 11.27 % actively doing so in third places, and 4.36 % within specific commercial third places (Fig. 10). While this study is conducted using Beijing as an example, the proposed approach is applicable to other regions with accessible data, including mobile phone big data and geospatial data. Selection criteria can be adjusted based on the local context, such as typical working hours on weekdays, workforce characteristics, and types of third places. Nevertheless, variations in socioeconomic attributes, cultural backgrounds,

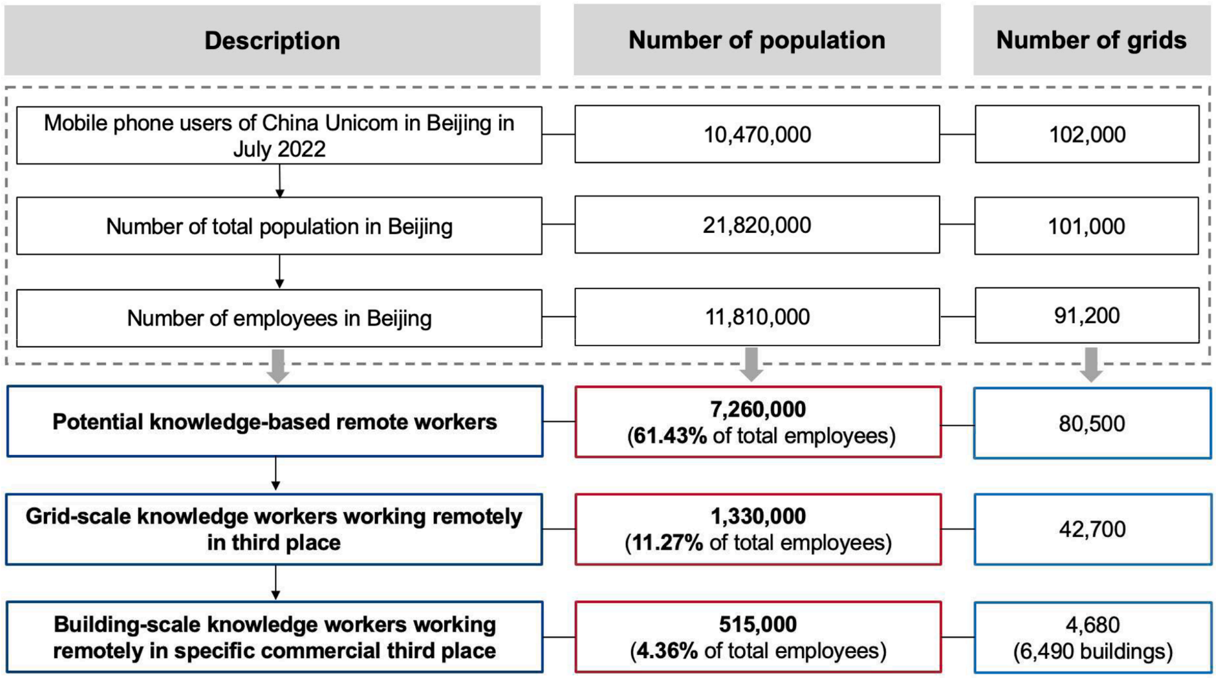


Fig. 10. Summary of each step for identifying third-place remote workers.

industry compositions, employment profiles, network infrastructure, and policies may lead to differing outcomes. The results drawn are particularly relevant to high-density international cities that house a substantial digital economy, and high-tech industries. These regions have a higher proportion of tertiary industry, large labor markets, and a quantity of knowledge workers, exhibiting greater potential for third-place remote work. The findings of this study hold the potential to assisting the establishment of urban design guidelines for hybrid work models and to the broader discourse on creating sustainable urban environments worldwide.

4.2. Comparison with previous studies

The findings regarding the proportion of knowledge workers engaging in remote work at third places in this study closely align with previous research outcomes. Primarily, the number of identified populations and employees coincided with the actual data in Beijing (Beijing Statistical Yearbook Committee, 2022). Prior to the pandemic, remote workers were estimated to constitute between 5 % and 10 % of the workforce (Leighton, 2021; Reuschke & Felstead, 2020). During the pandemic, the frequency of remote work significantly increased, with the percentage of employees working from home ranging from 35 % to 60 % (Eurofound, 2020; Bick et al., 2020). The U.S. Survey of Working Arrangements and Attitudes found that over 43 % of employees had worked in third places for some time in November 2021 (Caros et al., 2023). Currently, in the post-pandemic era, a majority of employees express a desire for more flexible work arrangements, enabling them to work from anywhere. Research has demonstrated that globally, 12–46 % of employees can work remotely, with approximately one-third to one-half of them opting for third places, amounting to 4–23 % (Gaskell, 2023; Lund et al., 2020). Notably, our calculated results, that is 11.27 % of employees actively utilizing third places and 4.36 % in specific commercial third places, fall within this range. Additionally, 38.60 % of the identified third-place remote workers work in specific commercial third places in our study, while 61.40 % of them may also use other third places as workplaces, such as friends' homes, others' offices, and public areas like parks. These hidden third places account for approximately 60 % of the total third-place utilization, in a survey estimate (Caros et al., 2023), further validating our findings.

Meanwhile, the result demonstrating a notable association between third-place visiting preference by remote workers and built environment aligns with prior relevant studies. Geographically, these third-place clusters are contingent upon fine-grained local economies, frequently situated at the fringes of creative hubs or urban centers and spreading outward later (Bassens et al., 2021). Popular third places are also determined by the urbanization degree, market size, transportation accessibility, business prospects, and skilled labor availability (Di Marino et al., 2018; Mariotti et al., 2017), exhibiting proximity to knowledge companies, residential areas, existing road networks, mixed-use and high-density areas (Coll-Martínez & Méndez-Ortega, 2023; Ge et al., 2018). Additionally, residents living in urban areas frequently visit cafés and fast-food shops, while community centers are more popular in proximate suburbs (Jeffres et al., 2009). Cafés stand out as preferred choices for remote workers, as supported by recent research from Swinburne University of Technology and Third-Place.org, which also indicates that participants occasionally visit libraries, parks, and coworking spaces (Hopkins, 2023).

4.3. Practical implications

Management measures and urban design strategies are imperative for developing hybrid work models, planning third places, and developing sustainable cities. From the urban planning perspective, urban networks need to be optimized through constructing a multi-centered spatial structure. Distributed and smaller third-place work hubs that harmonize with residential areas can also be proposed, thereby reducing real estate costs and commuting distances while enhancing working flexibility and spatial efficiency. Additionally, transportation accessibility needs to be enhanced by designing multifunctional spatial units that combine living, employment, and recreation, along with integrating diverse public transportation options (Di Marino et al., 2018; Wang & Ozbilen, 2020). This transformation can create diverse spatial combinations, provide flexible office spaces, and decrease commuting distances by making services easily accessible via public transport, walking, or cycling. This, in turn, helps reduce carbon emissions and energy use, contributing to the development of sustainable cities.

From the spatial design perspective, underutilized urban spaces and abandoned buildings can be revitalized as new third places to enhance spatial efficiency, especially as traditional office spaces are declining (Huang et al., 2020). Small-scale shared office spaces, such as Telecubes and Station Booths, characterized by assembly, modularity, and self-service, can be encouraged, providing independent workplaces anytime and anywhere. Third places should also incorporate essential features such as natural lighting, ample illumination, comfortable temperature, cozy furniture, high-speed Internet, accessible power outlets, dining options, and efficient services. These elements collectively create a welcoming atmosphere for both focused work and social interactions, making third places versatile as workplaces and social hubs (Jeffres et al., 2009).

From an industry management perspective, after adopting hybrid work models, reducing office space could be considered, potentially incorporating strategies like shared or rotating office desks. It will also be imperative to provide employee training and remote work applications. Looking ahead, the development of advanced technologies, such as artificial intelligence, extended reality, robotics and automation, and the increase of employees engaged in high-tech industries will be more beneficial to implementing remote work. The emergence of digital third places, such as cyberspace and the metaverse, will further augment the application for work from anywhere (Gabel & Mansfield, 2002). In the long term, companies, governments, and urban planners need to jointly develop enduring strategies for future hybrid work models.

4.4. Limitations

However, this study still has some limitations that warrant future research. Firstly, the data of mobile office app usage only provides aggregated monthly usage information, making it impossible to pinpoint the specific locations where remote workers use these apps. Therefore, the app usage is primarily used to identify knowledge workers capable of remote work. Additionally, the inability to record usage time when mobile data is inactive may slightly underestimate app usage duration. However, the proportion of Chinese users accessing the Internet via mobile phones has reached an impressive 99.8% (China Internet Network Information Center, 2023). With the advent of the 5 G era, faster internet speeds, and reduced data costs, the utilization of mobile data has become more widespread. As a result, even though there may be a slight underestimation in app usage duration, the impact on the selection of remote workers is negligible. Secondly, owing to the constrained precision of mobile phone signaling data (250 $m \times$ 250 m), there is a possibility that a third place located within the same building or very close to an individual's workplaces or residences might unintentionally be excluded when eliminating these locations. Meanwhile, capturing the full spectrum of remote work behaviors poses challenges. Therefore, subsequent research endeavors could delve into refining the spatial-temporal alignment of remote workers' behavior using wearable cameras, GPS trackers, and screen usage data, thereby surmounting the aforementioned constraints. Lastly, the association between third-place offices and other socioeconomic variables (e.g., educational background, income level) merits further exploration.

5. Conclusion

This study presents a quantitative approach to efficiently identify and characterize the fine-scale distribution of third places for remote work. The systematic approach involves identifying potential remote workers through mobile office app usage and delineating the distribution of third-place visits by remote workers at a fine scale, utilizing mobile phone signaling and geospatial data. Compared to other quantitative studies, this approach focuses on the emerging phenomenon of remote work in third places, providing faster and more extensive results on fine scales, from grid-level to building-level to indoor environments. At the grid scale, third places tend to cluster within innovation industry agglomeration zones. At the building scale, remote workers prefer to visit multifunctional buildings housing multiple third places with cafés, teahouses, or bookstores. At the indoor scale, the popular third places provide a conducive working environment, equipped with suitable furniture and essential amenities. Furthermore, this study analyzes the association between third-place preferences for remote work and the surrounding built environment using the XGBoost model and SHAP value. The findings from the case study in Beijing revealed that: (1) approximately 61.43 % of the total employees had the potential to work remotely, with 11.27 % actually opting for remote work in third places, and 4.35 % choosing specific commercial third places; (2) remote workers exhibited a preference for third places characterized by high-density mixed-use surroundings, proximity to residential communities, and convenient access to subway stations, among other built environment attributes. This study provides valuable insights for adopting a hybrid work model and benefits urban planners and designers in effectively designing third places, thereby contributing to the development of sustainable cities.

CRediT authorship contribution statement

Wenzhu Li: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Enjia Zhang:** Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Ying Long:** Conceptualization, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2024.105258.

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