

1 A Redesigned Approach to Job-Housing Spaces Identification in Urban
2 Areas Using Location-Based Service Data: A Case Study in Haidian
3 District of Beijing, China

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13 **Abstract:** Rapid urbanization promotes socio-economic development but also poses challenges for
14 urban management, particularly in achieving a balanced job-housing relationship. Such imbalances
15 can aggravate traffic congestion, increase energy consumption, and reduce commuting efficiency.
16 Addressing these urban issues requires accurate job-housing space identification (JHSI). The
17 emergence of spatiotemporal big data in geography has popularized location-based service (LBS)
18 data, especially mobile signaling data, for JHSI applications. However, using mobile signaling data
19 for JHSI faces challenges from dataset limitations and methodological complexities, such as data
20 inaccessibility caused by privacy issues. This study develops a redesigned JHSI approach using
21 another concise LBS dataset and changes the identification lens to focus on base stations. The newly
22 adopted dynamic population data covers simplified and privacy-sensitive fields, including only
23 information about base stations' geography and monitored population clusters. By establishing time
24 thresholds for working and living hours based on local daily routines and applying straightforward
25 statistical processing to these defined base station fields, we can derive estimated job-housing spaces.
26 We implemented this redesigned approach in Haidian District, Beijing, using five days of 2023 data
27 to evaluate the method's applicability and quantify job-housing imbalances at the Jiedao and town
28 scales. Results demonstrate the approach's accuracy – 66% for work identification and 80% for
29 residence identification – as well as its obvious advantages in concise, high-precision identification
30 with available data and in lightweight dataset applications with enhanced feasibility and broader
31 applicability. Finally, application scenarios are also discussed. We contend that this redesigned
32 method advances JHSI-related perspectives in macro-level daily research, facilitates further LBS-
33 driven urban applications, and contributes to improving human livability and quality of life in urban
34 areas.

35
36 **Keywords:** Urban areas; Population Dynamic Data; Job-Housing Space Identification (JHSI);
37 Location-Based Service (LBS) Data; Haidian District of Beijing

38
39 1 Introduction

40 With the development of urbanization, the function of urban areas has transformed from basic
41 living and production spaces into complex, multifunctional landscapes. As human-designed and
42 managed environments, urban areas demonstrate substantial differences in spatial organization
43 compared to natural ecosystems. As increasing numbers of people migrate to cities in pursuit of
44 better opportunities, high-quality job-housing spaces have emerged as a crucial metric for assessing
45 urban planning effectiveness and living standards. The job-housing spaces concept rose to
46 prominence following British sociologist Ebenezer Howard’s 19th-century “Garden City” proposal
47 (Howard, 1902). This model conceptualized urban environments where employment and residential
48 spaces were intentionally co-located to promote a balanced lifestyle. However, urbanization-related
49 issues continue to disrupt the job-housing balance in urban planning, posing growing challenges to
50 sustainable development and the balance between human activities and land use.

51 Rapid urbanization, characterized by large-scale population mobility and extensive urban
52 sprawl, has become the primary driver of spatial job-housing imbalance. This phenomenon aligns
53 with the spatial mismatch hypothesis (Kain, 1968) observed during American suburbanization.
54 Originally developed to analyze and quantify the growing spatial disparity between urban residential
55 locations and suburban employment opportunities (E. Wang et al., 2011), this hypothesis has
56 emerged as a critical concern in contemporary urban management (Schleith et al., 2016).
57 Consequently, numerous urban challenges have become prevalent, including severe traffic
58 congestion (Sultana, 2002; Li & Liu, 2016), reduced resident satisfaction, altered commuting
59 behaviors (Lin et al., 2015), prolonged commute times, and increased commuting costs (Yan et al.,
60 2019; Wang et al., 2021). Furthermore, research demonstrates that this imbalance exacerbates
61 environmental degradation (D. Wang, 2017). Particularly, reliance on private vehicles for daily
62 work-living travel has contributed to air pollution and other environmental problems in both
63 developed and developing nations (Guo et al., 2021; Zhou et al., 2016; Sun et al., 2015). China, as
64 the world’s second-largest economy (Lin et al., 2015), has undergone exceptionally rapid
65 urbanization since its 1978 economic reforms (Dong & Yan, 2021; Guan et al., 2018), with
66 urbanization rates increasing by nearly 50 percentage points between 1978 and 2023. This
67 transformation has made job-housing imbalance increasingly noticeable. Historically, before the
68 1990s, Chinese housing was primarily employer- or government-allocated and typically proximate
69 to workplaces. However, post-reform housing policies transitioned from state provision to market-
70 oriented systems (Guan et al., 2018; E. Wang et al., 2011; Zhou et al., 2016), leading to the current
71 prevalence of spatial separation between workplaces and residences. This shift has generated
72 substantial academic interest in China’s job-housing dynamics (Ta et al., 2017; E. Wang et al., 2011;
73 Zhou et al., 2016), particularly since the 1990s (Li & Liu, 2016; Ta et al., 2017). Additionally,
74 China’s commuting challenges are particularly severe and representative. The 2022 Annual Report
75 on Commuting Time in Major Chinese Cities reveals that over 70% of Chinese cities exceed 60
76 minutes in average daily commute time, with this figure continuing to rise. Given these
77 circumstances, understanding the relationship between job-housing spatial patterns and urban
78 development becomes crucial for effective urban land use management, environmental planning,
79 and accessibility enhancement transportation system design (Yao & Kim, 2022). Therefore, accurate
80 job-housing space identification (JHSI) serves as a vital quantitative foundation for addressing these
81 challenges and improving urban livability and quality of life.

82 The implementation of JHSI can be approached through two primary methodologies,
83 distinguished by their data sources and operational frameworks. The first approach employs

84 traditional statistical survey methods, including questionnaire surveys (Horner, 2002; Li & Liu,
85 2016; Long & Thill, 2015; Schleith et al., 2016) as well as population and economic censuses. The
86 second methodology leverages the growing application of spatial big data in geographical research,
87 which enables comprehensive, sophisticated, and multiscale urban analyses owing to its high
88 precision and spatially embedded social attributes. Among contemporary geographical big data
89 types, Location-Based Service (LBS) data have gained particular prominence. Comprising diverse
90 specialized datasets within LBS data with strong capabilities for monitoring human activities
91 through terminal positioning (Bi et al., 2023; Hadachi & Pourmoradnasseri, 2022; Mihaylova et al.,
92 2007; Rousell & Zipf, 2017; Schmidtke, 2020; Zhao & Gao, 2023), LBS data applications have
93 consequently attracted substantial research attention in JHSI and related urban studies. The accuracy
94 and scope of these applications continue to expand alongside the increasing volume of available
95 LBS-derived datasets. Common LBS datasets include: mobile signaling data from personal devices
96 (Ahas et al., 2010; Alexander et al., 2015; Yang et al., 2021), cellular network data (Isaacman et al.,
97 2011; Gundlegård et al., 2016; P. Zhang et al., 2017), vehicle GPS trajectory data (Mao et al., 2016;
98 Bi et al., 2023; Liu et al., 2020), Points of Interest (POI) data (Jiang et al., 2015; Y. Zhang et al.,
99 2021), internet-based positioning data (e.g., social media check-ins), public transportation tracking
100 data (e.g., smart card data) (Huang et al., 2019; Long & Thill, 2015; Sari Aslam et al., 2019), and
101 mobile phone trace data (Calabrese et al., 2013). Our study specifically focuses on comparative
102 analysis with mobile signaling data-driven JHSI approaches, as this data type has recently become
103 the most widely utilized LBS dataset in urban research. Beyond JHSI applications, mobility tracking
104 through these datasets serves multiple purposes, including mobility network estimation (Louail et
105 al., 2015), behavioral analysis (Calabrese et al., 2013; Ta et al., 2017; Yuan et al., 2012), commute
106 pattern studies (Yan et al., 2019), and examination of mobility-socioeconomic relationships (Zhao
107 & Gao, 2023). Nevertheless, JHSI implementation using mobile signaling data (Alexander et al.,
108 2015; Calabrese et al., 2013; Yang et al., 2021; Wang et al., 2020; Pei et al., 2014) and JHSI
109 implementation using traditional statistical censuses are facing notable challenges and limitations,
110 particularly concerning inherent dataset characteristics and methodological constraints of existing
111 JHSI approaches.

112 As the capital of China and a major international metropolis, Beijing has drawn considerable
113 scholarly and planning attention due to its rapid urbanization and complex spatial patterns in job-
114 housing relationships. Notably, the scale of the study area can significantly influence research
115 outcomes in urban job-housing spatial analysis, as demonstrated by Horner & Murray (2002) and
116 Small & Song (1992). In recent years, the intense pressures of urban life resulting from accelerated
117 urbanization have led districts to evolve into increasingly distinct agglomerations of urban lifestyles,
118 each with unique characteristics. However, prior research has predominantly focused on the city
119 scale (Zhao et al., 2011), leaving the spatial relationship between job-housing spaces and their
120 impact on daily life at the district or finer levels underexplored. Haidian District, one of Beijing's
121 sixteen administrative divisions, stands out due to its distinctive demographic profile and its leading
122 role in education and high-tech industries. The *Haidian District Planning (2017–2035)* underscores
123 the district's strategic importance, outlining specific targets for population control (limiting the
124 permanent population to 3.13 million by 2035), urban construction land use (capping urban and
125 rural land use at 2,270 km² by 2035), and coordinated functional spatial patterns. Furthermore, as a
126 critical component of the Beijing-Tianjin-Hebei (BTH) coordinated development strategy—which
127 aims to establish a world-class urban cluster in the region by 2030—Haidian District not only serves

128 as the primary hub for technological innovation to drive growth in Tianjin and Hebei but also
129 functions as a key relocation zone for Beijing’s non-capital functions. Given this strategic
130 positioning, effective management of job-housing spaces in Haidian is crucial for achieving these
131 multifaceted objectives.

132 In this study, we aim to accomplish two key objectives: (1) proposing a redesigned JHSI
133 approach that utilizes dynamic population data to address limitations in existing main LBS-driven
134 JHSI frameworks, and (2) implementing this approach through a district-scale case study in Haidian
135 District, Beijing, to analyze and map job-housing spaces while quantifying imbalance patterns
136 across its 22 Jiedaos and 7 towns (Jiedao is the administrative units similar to census tracts in the
137 U.S. are the basic spatial units in this study). For the first objective, we newly adopted a concise
138 LBS dataset—dynamic population data—which, like mobile signaling data, is derived from base
139 station signals but differs in its representation of aggregated population clusters rather than
140 individual trajectories. This dataset offers advantages in accessibility and privacy compliance, as it
141 avoids sensitive personal information. Furthermore, we shift the analytical perspective from
142 individual users to base stations in our redesigned JHSI framework. Instead of relying on movement
143 frequency during work and living periods, we classify base stations as either “working” or “living”
144 stations based on their monitoring patterns. This allows JHSI to be assessed through two dimensions:
145 (1) extracting geographical information and (2) estimating job-housing population distributions
146 based on the categorized base stations. Overall, this redesigned approach, leveraging dynamic
147 population data and an adjusted analytical lens, enhances cost-efficiency, processing speed,
148 feasibility, real-time updating capability, and broader applicability. For the second objective, we
149 apply the redesigned framework to Haidian District as a case study, generating quantitative insights
150 into job-housing relationships at a finer urban scale. Using dynamic population data from April 10–
151 14, 2023, we map the spatiotemporal distribution of job-housing spaces and employ the job-housing
152 balance index (JHB) along with its standard deviation (SD) to measure imbalance patterns. The
153 results reaffirm the method’s lightweight implementation and high accuracy. Finally, we discuss its
154 potential applications in urban planning, offering policy recommendations not only to address
155 population and housing challenges but also to support its integration into the Beijing-Tianjin-Hebei
156 (BTH) coordinated development strategy. In summary, the job-housing relationship represents a
157 crucial consideration in urban planning and policymaking for sustainable urban development.
158 Expanding upon the aforementioned studies, our research seeks to develop redesigned methods for
159 monitoring job-housing relationships across diverse scenarios and scales, thereby supporting both
160 daily commuting analysis and public policy applications. The study further enhances the
161 understanding of job-housing dynamics in key urban zones while promoting the application of
162 geospatial big data in urban planning and landscape design to mitigate housing-population conflicts.

163 The remainder of the paper is structured as follows. Section 2 provides a comprehensive review
164 of the main existing LBS-driven JHSI methodologies, along with theoretical frameworks for data
165 acquisition—including mobile terminal positioning technologies and the structural characteristics
166 of dynamic population data. Section 3, Materials and Methods, presents the methodological
167 framework and improvements for the redesigned JHSI approach. Section 4 presents the results of
168 the study conducted in Beijing’s Haidian District from April 10 to 14, 2023. Sections 5 and 6 present
169 the discussion and conclusions, respectively. The research flowchart is illustrated in Figure 1.

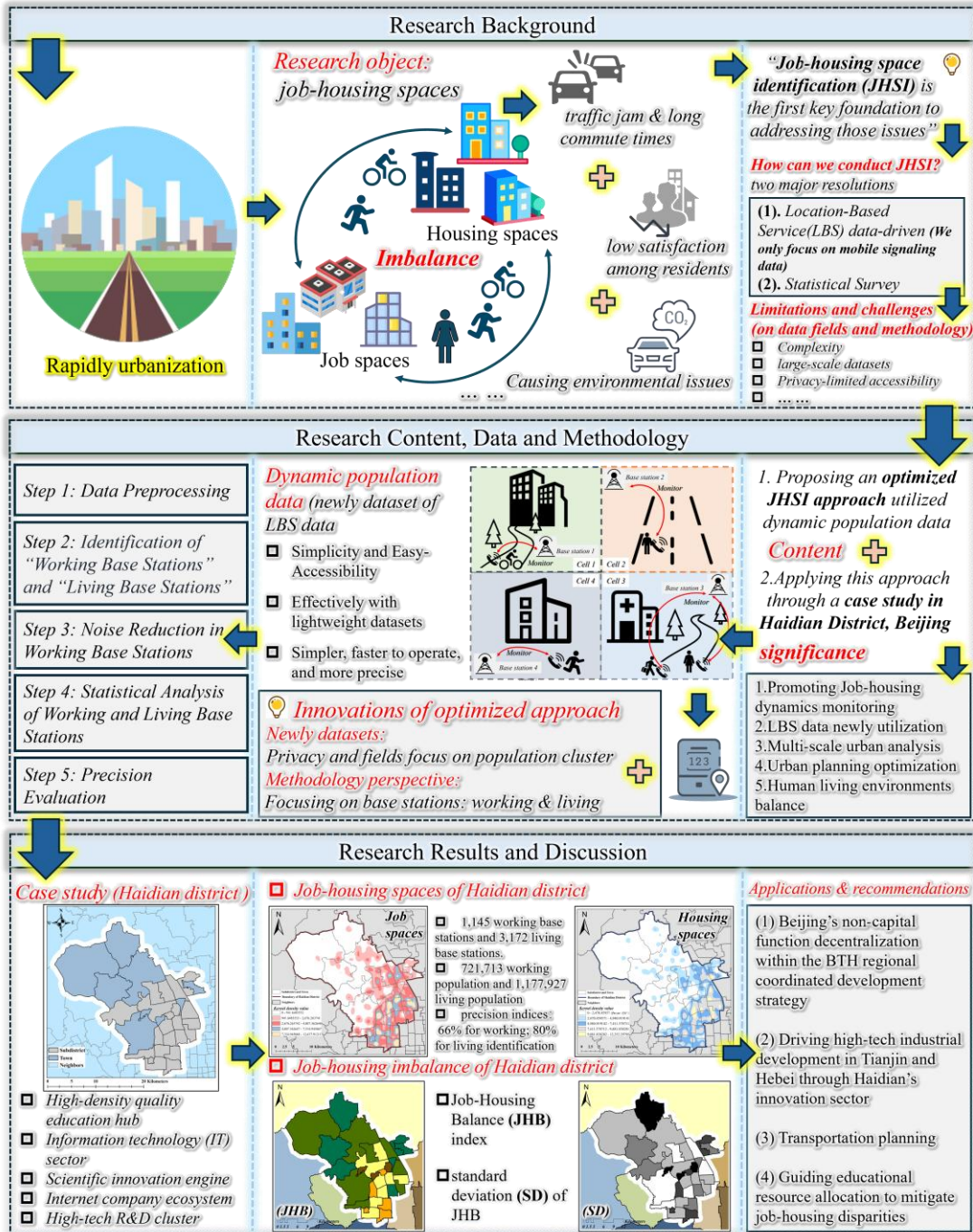


Figure 1: Flow chart of the research

2 Review of Existing JHSI Methodologies and Theories of Data

Acquisition

2.1. Methodological Frameworks of Existing JHSI

Among the existing frameworks for JHSI, first, we focus on comparing the LBS Data-Driven approach (we mainly focus on the most popular one, mobile signaling data), which primarily follows two methodological frameworks: (1) The most widely used framework relies on individual mobile phone users’ movement trajectories. Specifically, job-housing spaces are delineated by mining daily

179 commuting patterns between residential and workplace locations. First, thresholds for working and
180 living hours are established based on local daily routines. Next, the frequency of movement
181 trajectories—including locations and time periods—is statistically summarized for each user.
182 Finally, job-housing spaces are identified based on the prevalence of mobile users during working
183 and living hours. High-frequency locations during workday working hours are classified as
184 workspaces, while those dominant during living hours are designated as living spaces. The accuracy
185 of this approach heavily depends on the predefined time thresholds for working/living periods and
186 population mobility patterns (Alexander et al., 2015; Calabrese et al., 2013; Yang et al., 2021; Wang
187 et al., 2020). (2) The second framework utilizes aggregated mobile signaling data, analyzing call
188 volume records from base stations—including temporal distribution patterns and total volume—
189 over short periods (e.g., one week). By assessing communication activity patterns and applying
190 cluster analysis, this method infers land use types (e.g., residential and commercial zones, which
191 encompass job-housing spaces) within each base station coverage area, typically delineated using
192 Voronoi polygons and interpolated to grids (Pei et al., 2014). Secondly, regarding traditional
193 methodologies, they are entirely dependent on population groups defined by statistical work based
194 on such criteria as composite enterprise data, work registration records, and composite resident
195 population statistics—all within the administrative divisions of a panel perspective. Subsequently,
196 statistical outputs are generated based on different scales and timeframes, and the entire process is
197 relatively simplistic.

198 While both frameworks are currently employed in mobile signaling data analysis and
199 traditional statistical census analysis, they still face unresolved challenges: (1) Complex operations
200 on signaling data fields (e.g., DBSCAN and integrated complex cluster analysis), (2) limited
201 scalability across different spatial or temporal resolutions, (3) data acquisition barriers and high
202 costs due to privacy risks, (4) dependence on large-scale datasets, which impedes rapid JHSI
203 implementation and updates, and (5) insufficient precision in identification. Consequently,
204 optimizing both the dataset and the recognition logic within these frameworks remains the key
205 bottleneck in advancing research on job-housing relationship. (6) Traditional methods are
206 constrained by labor-intensive requirements, coupled with limited extrapolation capabilities,
207 primarily due to the delayed and low-frequency nature of data collection. Furthermore, the job-
208 housing relationship is anchored in the job-housing space as its carrier, representing a complex
209 dynamic involving population movement between workplaces and residences (i.e., commuting
210 flows). Traditional statistical approaches only separately measure the resident population and
211 employed population within a given area. However, from the perspective of population
212 agglomeration, the population in job-housing spaces mainly refers to residents with an employment
213 identity—along with their associated commuting flows. Regrettably, traditional statistical methods
214 fail to capture and reflect this critical layer of underlying information from a spatial perspective and
215 across different statistical scopes.

216 2.2 Theories of Data Acquisition

217 The rapid development of wireless communication and information technologies has driven
218 advances in geospatial and transportation-related research. Specifically, advancements in GIS, GPS,
219 and RS (3S) technologies have enhanced LBS, enabling it to conduct positioning using multiple
220 datasets from mobile terminal devices instead of traditional single-simplified spatial positioning
221 devices. This progress has significantly promoted geospatial services in commercial use(Liao &
222 Dong, 2017; Rousell & Zipf, 2017; Schmidtke, 2020; Weng et al., 2017). For example, Rousell and

223 Zipf (2017) created a prototype navigation service that uses LBS data (sets of landmarks from
224 OpenStreetMap) to generate pedestrian navigation instructions. Weng et al. (2017) proposed a
225 method to extract urban landmarks rapidly from spatial databases, using LBS data (sets of check-
226 ins and local accessibility) as weighted parameters. These examples demonstrate the tremendous
227 potential of LBS technology in urban planning and navigation services. Until today, the widespread
228 use of smartphones and advanced mobile positioning technologies has strengthened the importance
229 of location services by providing alternatives to traditional GPS-based methods, and research on
230 population mobility has expanded significantly (Hadachi & Pourmoradnasseri, 2022; Mihaylova et
231 al., 2007; Yuan et al., 2012). In this study, dynamic population data, another type of LBS data, has
232 not yet been widely used but has shown great potential. This data is obtained through base station
233 positioning technology monitored on mobile phones. In this section, we will detail the principles of
234 base station positioning technology and the structure of dynamic population data.

235 2.2.1 Base Station Positioning Technology

236 Base station positioning technology is based on the fundamental infrastructure of cellular
237 networks. This network divides the service areas into a cellular structure with each cell having its
238 own unique cell-ID. The cellular structure commonly has multitype shapes, Voronoi polygons are
239 one of the widely methods employed to divide the whole cellular network (Perera et al., 2015;
240 Sharifzadeh & Shahabi, 2006; Sharifzadeh & Shahabi, 2009; Pei et al., 2014). Base positioning
241 technology offers a simple, economical, and highly available solution with wide space-coverages
242 (both outdoors and indoors) without requiring any upgrades to handsets or network equipment,
243 unlike GPS or WiFi positioning technologies(Perera et al., 2015; Trevisani & Vitaletti, 2004).

244 In this study, the dynamic population data has been fuzzy processed because the geographic
245 locations of base stations are often irregularly distributed, and their data access is restricted in public
246 research. Specifically, grids composed of square cells with a resolution of $200\text{m} \times 200\text{m}$ were
247 established based on the original base station data. The geographic coordinates of the grid cells were
248 assigned to the base stations, allowing for spatial errors of 100 to 200 meters while maintaining only
249 one base station per cell. Although hexagonal cells are typically used in cellular networks for more
250 efficient coverage and reduced interference, we consider only square-cell networks where each cell
251 contains a single base station to prevent monitoring interference (Fig. 2).

252 Based on the above, we can obtain the simplified general form of LBS data from the following
253 principle: Specifically, when a visitor with a power-on mobile phone enters the serving area of a
254 base station, his information will be recorded, thus LBS data on all visitors will be produced. This
255 data is linked to the base stations by recording the visitor number within a certain period. The
256 geographic information of the LBS data is the exact location of the base station, identified by a
257 unique cell ID. The spatial precision of the data depends largely on the service area of the cellular
258 network (Trevisani & Vitaletti, 2004). For example, the locations of Base Stations 1 to 4 (Fig. 2) are
259 assigned to visitors with mobile phones when they enter the service area of the cell where the base
260 station is located. Along with other information, a row of LBS data for each visitor will be generated.
261 However, fast movement between base stations and staying time of the visitors will affect the
262 precision of LBS data. For instance, repeat recordings of the moving drivers in different base stations
263 will lead to error in LBS data. These effects often occur in certain LBS data, such as mobile signaling
264 data, which may become extensive and noisy during specific periods. Data processing techniques
265 are required to remove the noise, including ‘ping-pong switching’ analysis and clustering.

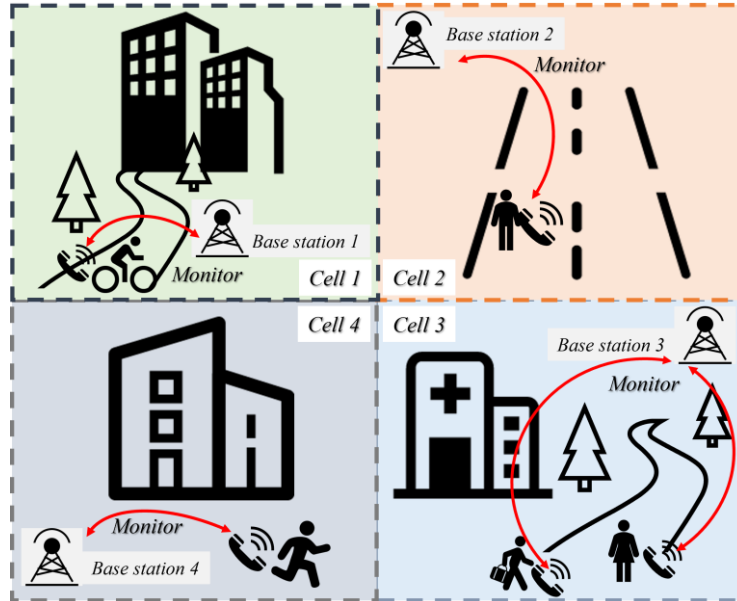


Figure 2: A Simplified View of the Cellular Network and four Examples of Base Station Monitoring

2.2.2 Overview of the Dynamic Population Data Structure

Dynamic population data is the sequence of population deduced from mobile phone signaling data. Mobile signaling data based on the monitoring functions of mobile base stations, is widely used in urban studies based on its diverse data attributes. These include unique IDs of each base station and the mobile phone users, personal information of mobile phone users (such as age), geographical location of base station, lasting time of the signal, and the types of mobile device (Okmi et al., 2023; Yang et al., 2021). In contrast, dynamic population data has more concise and general attribute about the base stations and mobile phone users. In this section, the overview of dynamic population data structure will be given in following 2 aspects:

1. Simplicity and Easy-Accessibility of Dynamic Population Data

Dynamic population data have simpler attributes than mobile signaling data. Only the key information of the mobile users is kept, such as the base station location (i.e., “longitude” and “latitude”), recording time (i.e., “Year-Day-Time”), the Administration Name, and the population number in each base station (i.e., “POPu”). In the dynamic population data, all information related to privacy is removed, making it more accessible to the publics compared to mobile signaling data.

2. More General and Simple Monitoring Principles of Dynamic Population Data

Compared with mobile signaling data, we utilized dynamic population data is based on general and simplified monitoring principles. It provides 24 recordings each day at one-hour intervals. Additionally, this principle avoids repeated recordings of the same visitor at the same base station within an hour and excludes useless short-period recordings. Only the recordings of the visitor who stayed the longest at a given base station within each hour will be retained. Table 1 gives a sample of dynamic population data from four base stations in Beijing’s Haidian District at 0:00 on April 10, 2023. The first row of Table 1 indicates that “20***” visitors were in the base station of (116. *****°E, 39.*****°N) in Haidian District of Beijing at 00:00, April 10th, 2023. This data is simpler compared to mobile signaling data. In mobile signaling data, information about User A and his personal details such as age “M”, location (Longitude, Latitude), and actions using the mobile from t_n to t_m are recorded in a field.

Table 1: Example of Dynamic Population Data Attribute Fields

Base station	Longitude	Latitude	Administration Name	Year-Day-Time	POPu
1	116.*****°E	39.*****°N	Haidian District, Beijing	2023-0410-00	20**
2	116.*****°E	39.*****°N	Haidian District, Beijing	2023-0410-00	15**
3	116.*****°E	39.*****°N	Haidian District, Beijing	2023-0410-00	15**
4	116.*****°E	39.*****°N	Haidian District, Beijing	2023-0410-00	13**

296 Note: This table presents a sample of dynamic population data monitored in the Haidian District, Beijing, with a
297 spatial resolution of 200m x 200m. The geographic coordinates are based on the WGS84 coordinate system. The
298 “****” is used for privacy protection.

299 This study employs dynamic population data that strictly adheres to *China’s Personal*
300 *Information Protection Law (PIPL)* and relevant regulations through comprehensive technical and
301 administrative safeguards. The dataset contains no sensitive personal information, as all collected
302 data were pre-aggregated and anonymized without including device IDs or any personally
303 identifiable information. All analyses were conducted exclusively at the aggregate level, ensuring
304 no individual behaviors could be traced. For spatial anonymization, raw base station positioning
305 data were processed into 200m×200m grids, with system-generated grid centroids offset by at least
306 100m from actual base station locations, while temporal resolution was reduced to 1-hour intervals
307 to further enhance privacy protection. The data processing protocol fully complies with the
308 anonymization requirements specified in GB/T 35273-2020 *Information Security Technology -*
309 *Personal Information Security Specification*, ensuring complete regulatory compliance.

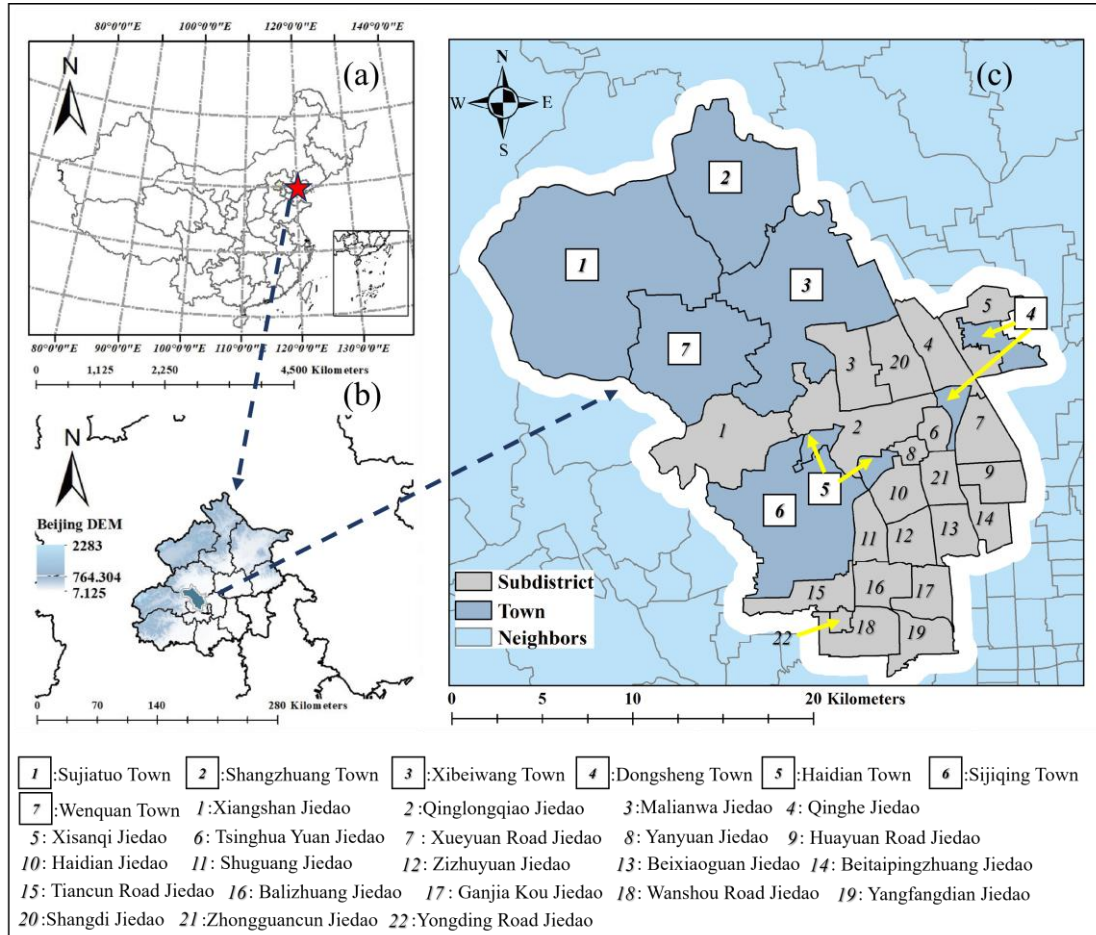
310 3 Materials and Methods

311 3.1 Study area

312 Haidian District, one of Beijing’s sixteen administrative districts, is situated in the northwestern
313 and western parts of the city, covering an area of approximately 430.8 km². As of 2023, it had a
314 permanent population of 3.125 million, accounting for about 2.6% of Beijing’s total area. In the
315 same year, Haidian’s GDP reached 1,102.02 billion RMB, representing 25.2% of Beijing’s total
316 GDP (Haidian District Statistics Bureau 2024, 2024). The district is strategically positioned as a hub
317 for high-quality education (hosting more than eighty universities), information technology, and
318 scientific innovation. According to the Haidian District Planning (2017–2035), the area is slated to
319 become a pivotal zone for China’s political culture, technological advancement, and economic
320 expansion. It has already emerged as a major center for internet companies and high-tech research
321 and development (R&D). However, the rapid growth of education and internet technology has also
322 accelerated urbanization, leading to associated urban challenges in Haidian District.

323 Administratively, Haidian consists of 22 Jiedaos and 9 towns, each exhibiting distinct
324 characteristics that contribute to a diversified development pattern. Data from the Haidian District
325 Fourth National Economic Census Major Data Bulletin (2020) and the Haidian District Seventh
326 National Population Census Bulletin (2021) highlight some key areas: Zhongguancun Jiedao is
327 renowned for its innovation-driven ecosystem, housing 19,250 legal entities in secondary and
328 tertiary industries as of 2018. Haidian Jiedao, home to prestigious institutions such as the Chinese
329 Academy of Sciences, Peking University, and Tsinghua University, serves as an academic and
330 research nucleus. Xueyuan Road Jiedao had a permanent population of 226,315 in 2020 and is
331 distinguished by its concentration of higher education institutions. Beixiaguan Jiedao and
332 Zizhuyuan Jiedao, with populations of 146,366 and 129,367 respectively, attract residents and
333 businesses due to their cultural and educational amenities. Ganjiakou Jiedao stands out as the most
334 economically dynamic, with total assets amounting to 2,297.73 billion RMB in 2018. Qinghe Jiedao

335 and Xisanqi Jiedao have experienced rapid development, recording populations of 147,395 and
 336 157,643, respectively. Meanwhile, Sijiqing Town and Xibeiwang Town exhibit high population
 337 densities, with 162,700 and 164,795 residents as of 2020. Figure 3 illustrates the study area,
 338 featuring a 90m digital elevation model (DEM) of Beijing and highlighting the spatial distribution
 339 of Jiedaos and towns within Haidian District.



340
 341 Figure 3: Study Area of Haidian District

342 Note: (a) The location of Beijing in China; (b) The location of Haidian District in Beijing with 90m DEM; (c) The
 343 composition of Haidian District with detailed Jiedao information. All geographic data were collected from the
 344 Geospatial Data Cloud (<http://www.gscloud.cn>) and the National Platform for Common Geospatial Information
 345 Services (<https://www.tianditu.gov.cn/?4>).

346 3.2 Data Sources

347 In this study, two types of datasets are used: the LBS datasets and the statistical datasets.
 348 Specifically, the descriptions and sources of dynamic population data, permanent resident
 349 population, employee population, other population, and aging population are all shown in Table 2.
 350 Among them, the dynamic population data was utilized from April 10th to April 14th, 2023 (five
 351 consecutive workdays, not including the effects of holidays or other factors).

352 Table 2 Data Sources in this Case Study

Data Type	Description	Data Source
Dynamic population data	Data is organized into 200m x 200m grids, from April 10 th to April 14 th , 2023, in Haidian District.	The dynamic population data was provided by a licensed telecommunications service provider in China under anonymized processing.

Permanent resident population	The 2023 permanent resident data for Haidian District (preprocessed with other and aging population) provided the reference for comparing of identified living population results.	Beijing Statistical Yearbook (2024): [https://nj.tjj.beijing.gov.cn/nj/main/2024-tjnj/zk/indexch.htm]
Employed population	Haidian District's 2023 year-end urban non-private sector employment data served as the reference for comparing with identified working population results.	Beijing Regional Statistical Yearbook (2024): [https://nj.tjj.beijing.gov.cn/nj/qxnj/2024/zk/indexch.htm] (in Chinese)
Other population	Haidian District's 2023 year-end 0-14 age population data served as a proxy for non-working residents and was used as exclusion criteria when preprocessing the permanent resident dataset for precision evaluation.	Beijing Regional Statistical Yearbook (2024): [https://nj.tjj.beijing.gov.cn/nj/qxnj/2024/zk/indexch.htm] (in Chinese)
Aging population	Haidian District's 2023 elderly population (65+) statistics served as a proxy for non-working residents and were used as exclusion criteria when preprocessing the permanent resident dataset for precision evaluation.	Beijing Regional Statistical Yearbook (2024): [https://nj.tjj.beijing.gov.cn/nj/qxnj/2024/zk/indexch.htm] (in Chinese)

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3.3 Methods

3.3.1 Redesigned Framework for JHSI Using Dynamic Population Data

Step 1: Data Preprocessing

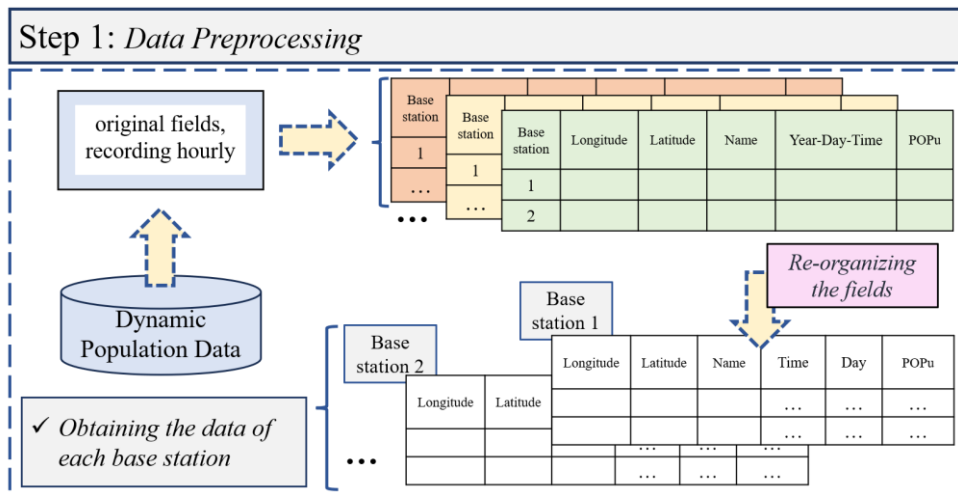
The dynamic population data in Table 1 is originated from the monitoring records of all base stations. This step involves re-organizing the attribute fields of the data from the base stations (Fig. 4). It aims to ensure all the records of same base station being grouped into one dataset. Additionally, the fields “Day” and “Time” are separated from the “Year-Day-Time” field for further analysis. For example, Table 3 gives an example of organized data attribute fields by data preprocessing, the population number monitored by the base station 1 with (116.*****°E, 40.*****°N) in four periods: 2 AM, 3 AM, and 4 AM on April 10th, and 9 AM on April 11th was identified.

Table 3: Example of Organized Data Attribute Fields.

Base Station	Longitude	Latitude	Administration Name	Time	Day	POPu
1	116.*****°E	40.*****°N	Haidian District, Beijing	2	410	9**
1	116.*****°E	40.*****°N	Haidian District, Beijing	3	410	7**
1	116.*****°E	40.*****°N	Haidian District, Beijing	4	410	6**
1	116.*****°E	40.*****°N	Haidian District, Beijing	9	411	15**

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Note: This table presents a sample of dynamic population data monitored in the Haidian District, Beijing, with a spatial resolution of 200m x 200m. The geographic coordinates are based on the WGS84. The “****” is used for privacy protection.

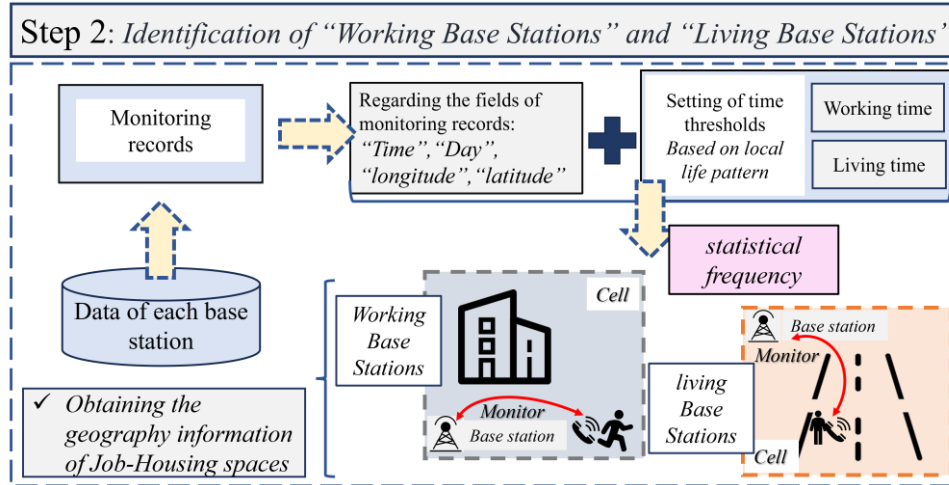


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Figure 4: Data Preprocessing in the redesigned JHSI Framework

Step 2: Identification of “Working Base Stations” and “Living Base Stations”

370 In this step, thresholds for working and living time are established based on the daily life
 371 patterns of local residents. Specifically, we first calculate the frequency at which each base station
 372 operates within these predefined working and living time thresholds; subsequently, each base station
 373 is classified as a working or living base station based on this statistical frequency (Fig. 5). After the
 374 working base stations and living base stations are defined, the spatial pattern of job-housing spaces
 375 can be derived. In practice, the location of the working and living base stations will be used as symbols
 376 of the location information of job-housing spaces, respectively.



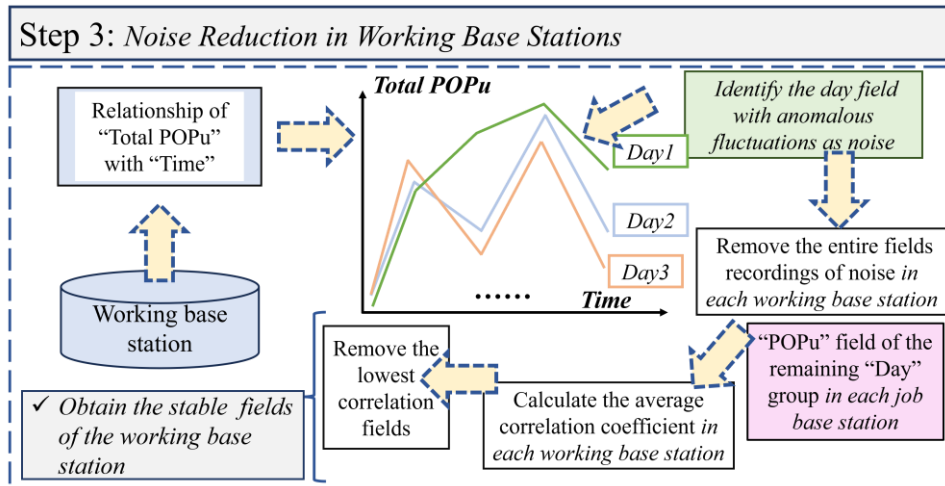
377
 378 Figure 5: Identification of "Working Base Stations" and "Living Base Stations" in the Redesigned JHSI
 379 Framework

380 Step 3: Noise Reduction in Working Base Stations

381 Before the statistical process, it is necessary to remove noise information from working base
 382 stations for better accuracy. This is because population dynamics during working hours are more
 383 regular at working base stations compared to living base stations. Additionally, due to the large
 384 population flow in urban areas—particularly amplified by political and economic factors such as
 385 suburban urbanization and the planning of industrial agglomeration zones—there exists a
 386 considerable span of job-housing mobility in many urban regions. Moreover, during non-working
 387 hours, people's travel purposes involve more subjective factors, and the fields of dynamic
 388 population data do not support continuous tracking of individual tracks. In this context, given that
 389 base stations themselves are fixed in location, the hourly population record represents the individual
 390 with the longest stay within that hour. Thus, we only performed noise reduction on working base
 391 stations. Meanwhile, for living base stations, we strive to exclude subjective and occasional errors
 392 and ignore errors caused by free population movement by selecting the optimal "Living time period"
 393 based on the study area of the chosen city.

394 A group of all working base stations is organized by the "Day" field, as shown in Table 3. The
 395 detailed procedure is as follows (Fig. 6). Firstly, based on all job base stations, we calculate the total
 396 "POPu" field for each "Day", referred to as "Total POPu". Then, the relationship between the "Time"
 397 field and the "Total POPu" is established to identify the general trends of this relationship. Secondly,
 398 one or more "Day" groups with significant fluctuation anomalies, which show trends obviously
 399 different from other "Day" groups, will be identified as noise. After that, we remove the entire field
 400 recordings of the noise in each working base station. Finally, in each base station, we calculate the
 401 average correlation coefficient for the remaining "Day" groups and remove the entire field
 402 recordings of the "Day" group with the lowest average correlation coefficient. The remaining fields

403 in each working base station are then utilized for further analysis.

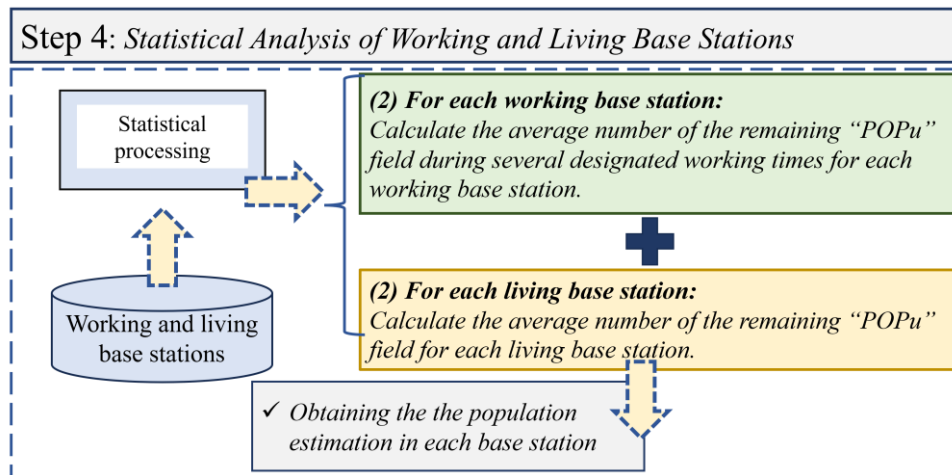


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Figure 6: Noise Reduction in Working Base Stations in the redesigned JHSI Framework

406 Step 4: Statistical Analysis of Working and Living Base Stations

407 Based on the previous step, the geographical spatial information of working-living spaces was
408 obtained. In this step, the final population estimation for each working and living base station will
409 be determined through data processing and statistical analysis (Fig. 7). Specifically, the average
410 number of the remaining “POPu” field will be calculated based on the living time at each living
411 base station. Additionally, due to the significant characteristics of population mobility during
412 working hours, the average number for working base stations will be calculated during several
413 designated working times, such as 8 am, 11 am, and 4 pm(Yang et al., 2021).



414

Figure 7: Statistical Analysis of Working and Living Base Stations in the redesigned JHSI framework

416 Step 5: Precision Evaluation

417 Current research on JHSI often inadequately addresses precision evaluation (Zheng et al.,
418 2023). Given the strong correlation between dynamic population data and mobile signaling data,
419 this study adopts a precision evaluation framework for mobile signaling data-driven methods,
420 emphasizing consistency between identified job-housing population distributions and the actual
421 spatial logic of the study area (Fig. 3). Specifically, precision is verified by comparing regional
422 living/working population statistics with identification results in terms of quantitative relationships
423 (Wang et al., 2020). Two key considerations emerge: (1) Data representativeness: Dynamic
424 population data primarily reflects mobile user monitoring, with coverage limited to specific carrier

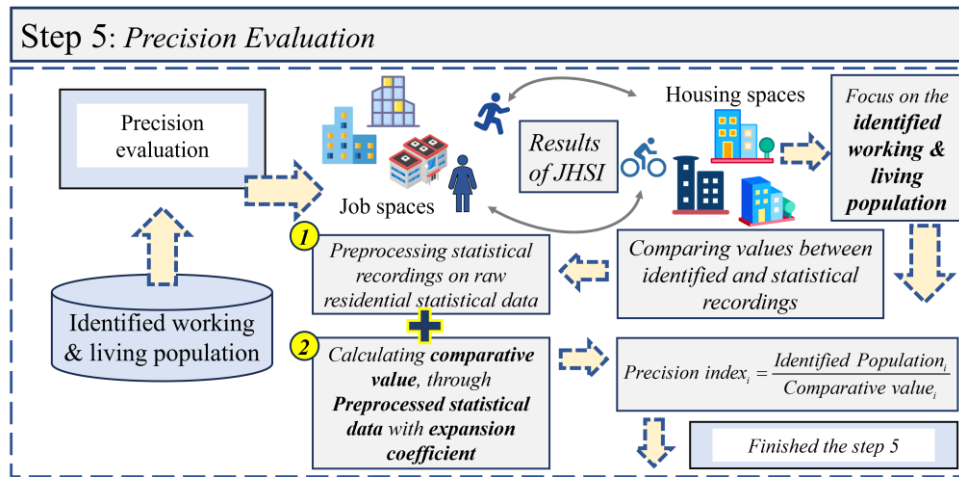
425 subscriber groups. Due to privacy constraints, obtaining complete datasets from all carriers remains
 426 challenging (not all provide well-protected dynamic population data). Thus, this study applies a
 427 scaling method using an “expansion coefficient” (estimated 60–70%) derived from
 428 telecommunications operation-related market statistics to align coverage with actual user
 429 proportions. (2) Statistical data preprocessing: Since job-housing relationships describe spatial
 430 connections between workplaces and residences of employed populations, non-working residents
 431 must be excluded from raw residential statistics before precision evaluation but retaining
 432 unprocessed employment data. Considering China’s compulsory education, age structure, and
 433 retirement policies (60 for men, 55 for women), we exclude populations aged 0–14 and over 65
 434 from raw statistics before expansion coefficient adjustment to derive the final “comparative value”
 435 (Formula (1)). This standardized methodology ensures indicator comparability and rigorous
 436 precision evaluation.

437 Based on this framework, JHSI precision is evaluated by calculating a precision index using
 438 the identified populations and comparative values (Formula (2)), with the full process illustrated in
 439 Figure 8. Note that temporal mismatches between statistical surveys and identification results
 440 introduce unavoidable time-lag errors, which should be minimized where possible.

441
$$\text{Comparative value}_i = \text{Expansion coefficient} \times \text{Processed Statistical data}_i \quad (1)$$

442
$$\text{Precision index}_i = \frac{\text{Identified Population}_i}{\text{Comparative value}_i} \quad (2)$$

443 In Formula (1) and (2), the subscript i , covers both working and living scenarios, which
 444 respectively correspond to the employment-related and residence-related population values
 445 processed in the aforementioned steps.



446
 447 Figure 8: Precision Evaluation in the redesigned JHSI framework

448 3.3.2 Improvement of the Redesigned JHSI Approach with Dynamic Population Data

449 Compared to existing JHSI approaches based on LBS data, particularly those relying on mobile
 450 signaling data, our redesigned method offers notable advancements. (1) The redesigned JHSI
 451 approach is simpler, faster, and more precise. Dynamic population data employs straightforward
 452 fields (e.g., the “POPu” field for population mobility clustering), reducing data processing
 453 complexity. The method focuses on each base station—which have fixed locations—enabling rapid
 454 implementation and broader regional-scale applicability. Unlike mobile signaling data driven that

455 require substantial computational resources and clustering algorithms (e.g., DBSCAN), the
456 redesigned JHSI framework is user-friendly and adaptable to diverse urban contexts. Furthermore,
457 since dynamic population data contains no personally identifiable information, it is highly accessible,
458 allowing the method to function as a simple, single-source-driven solution. Additionally, our
459 approach more efficiently defines base stations from a functional perspective while using
460 straightforward statistical processing to identify stable monitoring trends. This simplifies complex
461 operations such as supervised classification and clustering while establishing a foundation for high-
462 precision identification (particularly in contrast with the work of Pei et al., 2014). (2) The redesigned
463 JHSI framework performs effectively with smaller sample sizes. By shifting the analytical focus to
464 spatially stable base stations—rather than individual mobility patterns—the method enables feasible
465 implementation with lightweight datasets. In contrast, traditional approaches relying on mobile
466 signaling data often demand larger samples (e.g., Wang et al., 2020, who used one month of mobile
467 signaling data). The reduced data requirements also facilitate dynamic monitoring and significantly
468 shorten update cycles. (3) The redesigned JHSI approach demonstrates higher feasibility and
469 broader applicability. Many LBS datasets are restricted due to corporate or institutional ownership
470 and high access costs, limiting their availability to public and independent researchers. In contrast,
471 dynamic population data is more accessible, cost-effective, and suitable for routine use by public
472 and non-institutional organizations across various scenarios. Since it excludes sensitive user
473 information or detailed activity records, the method enhances the practicality of JHSI applications.
474 Moreover, it supports multi-scale adjustments based on research needs, enabling further
475 investigations into job-housing imbalances and spatial functionality at finer scales.

476 At last, when compared to the traditional JHSI studies that rely on population censuses, our
477 redesigned approach stands out. Unlike the periodic panel surveys adopted in traditional
478 demography, our method not only achieves labor savings and rapid periodic updates but also enables
479 the efficient spatialized expression of population agglomeration, thereby facilitating the
480 identification of job-housing spaces. Additionally, by shifting the identification perspective to base
481 station data and incorporating the “working” and “living” time period settings, the definition and
482 identification of population clusters can embody the attribute that the population in job-housing
483 spaces mainly refers to residents with an employment identity.

484 3.3.3 Parameter Setting for the Application of the Redesigned JHSI Framework in 485 Haidian District

486 Firstly, the thresholds and statistical time periods for defining working and living base stations
487 are given. Specifically, according to the *Third National Time Use Survey Bulletin (No. 3)* released
488 by *China's National Bureau of Statistics* in 2024 (National Bureau of Statistics of China, 2024), the
489 survey analyzed residents' weekly time allocation across major life domains including paid work,
490 unpaid labor, and transportation, with breakdowns by age group, gender, and household registration
491 status (urban/rural). The data reveals that urban and rural residents averaged 6 hours 23 minutes and
492 6 hours 22 minutes of daily paid work respectively, with the working-age population (18-59 years)
493 reaching 6 hours 32 minutes per day. For essential physiological activities, all demographic groups
494 maintained a consistent daily average of approximately 12 hours 30 minutes, never dipping below
495 12 hours. Building upon these statistical recordings and incorporating the commute time thresholds
496 established by Chinese researchers in JHSI-related studies (Table 4), we have accordingly set
497 temporal parameters for job-housing patterns in Haidian District. In our study, the working time
498 period was set from 7:00 am to 5:00 pm on workdays, and the living time period was set from 9:00

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pm on the previous workday to 5:00 am on the next workday.

Table 4 Literature Parameters for Working and Living Time Thresholds

Time Segment Threshold	Threshold Value	Statistical Time Frame	Reference Source
Working time period	9:00-17:00, 8:00-18:00	Recurring for ≥ 10 days	(Wang et al., 2020), (Zheng et al., 2023)
Living time period	21:00-7:00(next day), 21:00-8:00(next day), 0:00-6:00, 20:00-5:00(next day)	Recurring for ≥ 10 days (or ≥ 15 days)	(Wang et al., 2020), (Zheng et al., 2023), (ZHANG et al., 2023)

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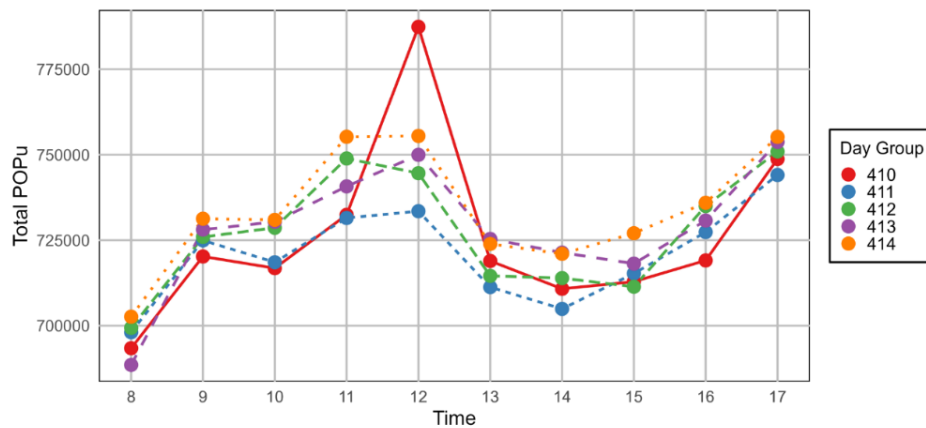
Note: While the referenced studies in Table 4 analyzed monthly data, our study employs weekly observations to enable finer-grained temporal analysis.

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Secondly, for identifying working and living base stations: When a base station conducts monitoring with full performance throughout the entire working time period on each research workday, it will be designated as a working base station. However, due to the complex regular trends of population mobility during living time, if a base station conducts monitoring that matches the living patterns of Haidian District—i.e., at six or more time points during each living time period on a full research workday—it will be designated as a living base station.

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Finally, for noise reduction and statistical processing, we plotted a trend of the “Time” field against “Total POPu” for each “Day” in all working base stations (Fig. 6). After observing the regular trends in these relationships, an obvious fluctuation with a different trend was identified in the records of April 10, which was classified as noise (Fig. 9). Then, all the records of the noise were removed from each working base station. Additionally, in the final data processing for working base stations, based on step 4 on section 3.3.1 and table 4, the selected working time points to calculate the average number of the “POPu” field, as an estimate of the working population, are 8:00 am, 11:00 am, and 4:00 pm (Zheng et al., 2023).



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Figure 9: Trend Analysis for All Job Base Stations on “Total POPu” and “Day Group”

3.3.4 Calculating of Job-Housing Imbalance

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After completing the procedure, the urban job-housing spaces will be identified, including information on working and living locations, as well as the job-housing populations. Then, we can observe the overall distribution of job-housing spaces through visualization. Additionally, the more detailed imbalance in job-housing spaces at finer scales, such as Jiedaos and towns, can be quantified by calculating indices of job-housing imbalance, commonly using the Job-Housing Balance (JHB) index and its standard deviation (SD) (formulas (3) and (4)) (Weitz et.al, 1997; Wang et.al, 2022).

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$$JHB_{ij} = \frac{W_{ij} / W_i}{L_{ij} / L_i} \quad (3)$$

527
$$SD = |JHB_{ij} - 1| \quad (4)$$

528 In formula (3) and (4), JHB_{ij} represents the JHB index for Jiedaos or towns j in district i .
 529 W_{ij} denotes the number of employed people in Jiedaos or towns j in district i , while W_i is the
 530 total number of employed people in district i . Similarly, L_{ij} indicates the number of residents in
 531 Jiedaos or towns j in district i , and L_i is the total number of residents in district i .

532 If $JHB_{ij} = 1$, it indicates that the employment and residential functions are matched. If $JHB_{ij} > 1$,
 533 it means the proportion of employed people is higher than that of residents, suggesting that the
 534 employment function is stronger than the residential function. Conversely, if $JHB_{ij} < 1$, it indicates
 535 that the residential function is dominant. Additionally, the standard deviation (SD) of the JHB index
 536 can be used to measure the degree of job-housing spatial matching in the area. A smaller SD value
 537 indicates a better match between working and living spaces, while a larger SD value indicates a
 538 poorer match between them.

539 4 Results

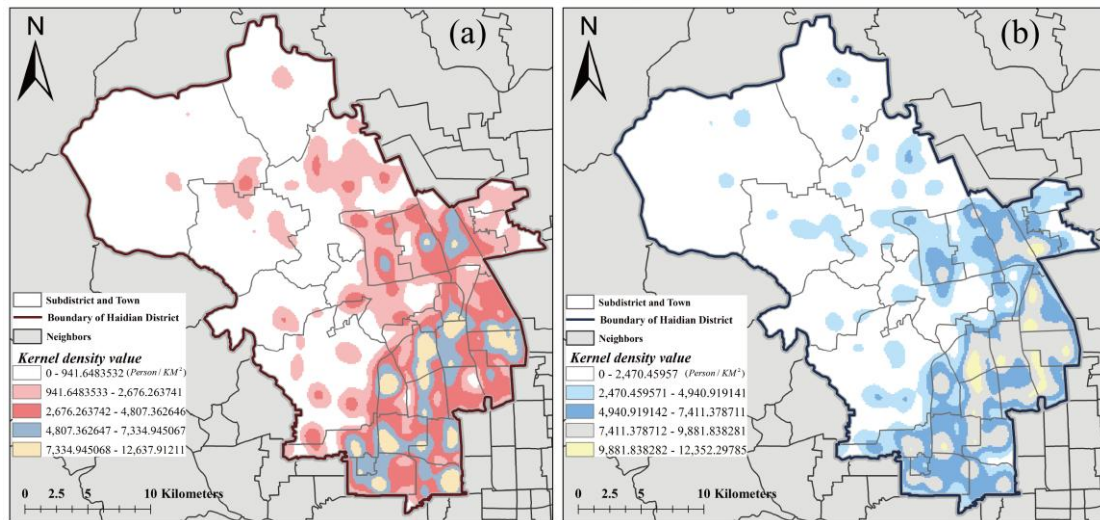
540 4.1 The Results of JHSI in Haidian District

541 Based on the defined steps and time thresholds, the job-housing spaces in Haidian District,
 542 Beijing, were identified, and their spatial distribution is illustrated using kernel density maps in Fig.
 543 10 (a) and (b). The analysis classified 1,145 base stations as working base stations and 3,172 as
 544 living base stations. In terms of population distribution, the estimated working population in Haidian
 545 District was approximately 721,713, while the living population was around 1,177,927. As shown
 546 in Fig. 10, the kernel density maps clearly reveal the spatial patterns of job-housing distribution,
 547 with concentrations primarily observed in the northern, eastern, and southeastern parts of Haidian
 548 District. The smaller spatial extent of residential areas compared to workplaces, combined with the
 549 kernel density analysis, suggests a notable imbalance between job and housing distributions.

550 To evaluate the precision of our estimates, we followed the methodology outlined in Step 5
 551 (Section 3.3.1) and referenced the statistical data source in Table 2. According to official statistics,
 552 Haidian District had a permanent resident population of 3.125 million in 2023, consisting of 1.684
 553 million employed individuals, 0.484 million elderly residents, and 0.371 million other populations.
 554 To ensure comparability with the dynamic population dataset, we applied an expansion coefficient
 555 of 65% to adjust the statistical figures. After calibration, the working and living populations were
 556 estimated at approximately 1,094,600 and 1,475,500, respectively. When compared to our dynamic
 557 population-derived results, discrepancies of 372,887 (working population) and 297,573 (living
 558 population) were observed, yielding precision indices of 66% for working population identification
 559 and 80% for residential population identification. Despite these differences, the overall trends
 560 remain consistent, and the margin of error is within an acceptable range for job-housing space
 561 analysis from comparable studies (e.g., Wang et al., 2020). Potential sources of discrepancy include
 562 the incomplete exclusion of non-working residents and the absence of real-time employment records

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for private-sector workers in the current statistical indicators used to represent occupational populations (Table 2).



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Figure 10: Kernel Density Map of Urban Working Spaces (a) and Living Spaces (b) in Haidian District

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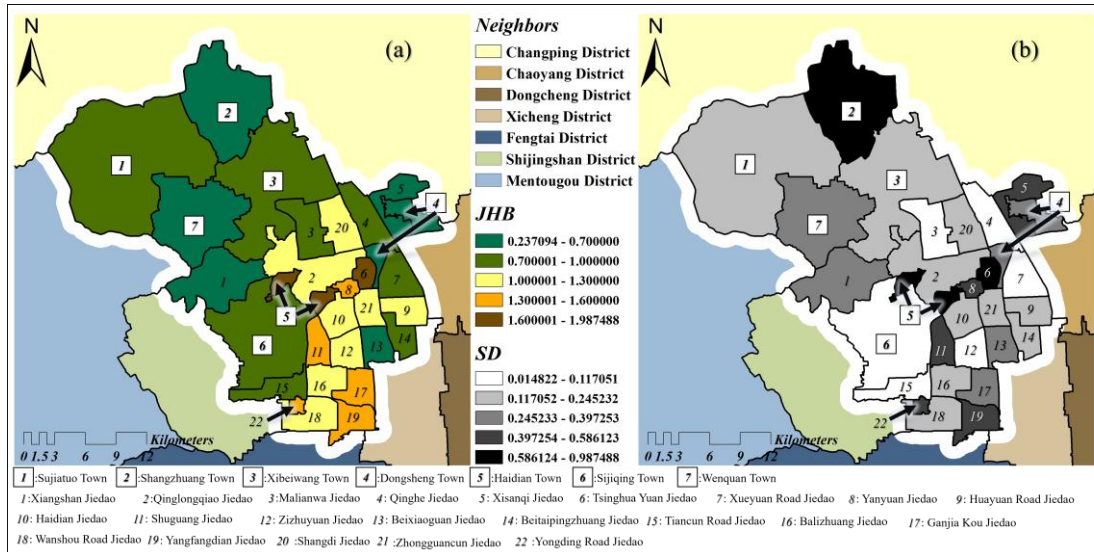
4.2 The Results of Job-Housing imbalance Calculation in Haidian District's 22 Jiedao and 7 Towns

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Based on the redesigned JHSI framework results from Section 4.1 and Formulas (3)-(4), we computed the JHB and SD indexes for Haidian District, representing working-living functional intensity and job-housing spatial imbalance patterns respectively. Following the methodology in Section 3.1, we established five classification intervals to distinguish areas with JHB values below or above 1 (Figure 11a). The JHB values in Haidian District range from 0.237094 (Shangzhuang Town) to 1.987488 (Haidian Town), exhibiting relatively compact spatial patterns without fragmented distribution. Specifically, 8 Jiedaos and 6 towns with $JHB < 1$ occupy most of Haidian's periphery, particularly at district boundaries: northern/northeastern (adjacent to Changping District), western (bordering Shijingshan and Mentougou Districts), and eastern (neighboring Chaoyang District). This category includes Jiedaos with values approaching 1, such as Xueyuan Road (0.985178), Malianwa (0.963796), and Tiancun Road (0.961074). Conversely, 14 Jiedaos and 1 town with $JHB > 1$ form a compact cluster in southern Haidian, predominantly showing values between 1-1.5. While Zizhuyuan Jiedao (1.079088) approaches balance, areas like Zhongguancun (1.155604), Shangdi (1.194954), and Yongding Road (1.517918) demonstrate clear employment dominance. Overall, job-concentrated areas are orderly distributed in eastern/southeastern Haidian, proximate to Beijing's central districts (Dongcheng, Xicheng, and Chaoyang).

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For SD analysis, we applied natural breaks classification to categorize the 29 values into five groups (Figure 11b). Haidian Town shows the maximum SD (0.987488), while Xueyuan Road Jiedao has the minimum (0.014822). The SD distribution across 22 Jiedaos and 7 towns reveals a highly fragmented spatial pattern, with most areas ranging 0.117052-0.245232. The most imbalanced areas include Haidian Town (0.987488), Tsinghua Yuan Jiedao (0.970939), and Shangzhuang Town (0.762906) - the latter being residence-dominated while the former two are employment-centered. Yongding Road Jiedao (0.517918) exhibits notably higher imbalance than Zhongguancun (0.155604) and Shangdi (0.194954). Furthermore, most boundary areas adjacent to Beijing's central districts (Chaoyang, Dongcheng, Xicheng, and Fengtai) display relatively high SD values, indicating pronounced job-housing imbalance.



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Figure 11: Distribution of the Job-Housing Balance (JHB) Index (a) and its Standard Deviation (SD) (b) at the Jiedao and Town Scale in Haidian District

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5 Discussion

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5.1 Spatial Distribution of Job-Housing Relationships in Haidian District

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The spatial distribution of job-housing relationships in Haidian District is illustrated through two maps: the distribution of job-housing spaces (Fig. 10) and imbalance patterns (Fig. 11). First, the analysis of job-housing spaces reveals distinct clustering patterns, with employment concentrations primarily located in two key regions: the northwest (e.g., Northwest Wang Town, Wenquan Town, and Sujiatuo Town), the southern and southeastern zones adjacent to Shijingshan, Chaoyang, Changping, and Beijing’s core urban districts (Dongcheng and Xicheng) (Fig. 10). This spatial arrangement aligns with Haidian’s industrial planning, as documented in the *Beijing Industrial Layout Map* (Beijing Municipal Development and Reform Commission, 2024). Specifically: (1) The Zhongguancun Future Science Park—specializing in next-generation IT, intelligent connected vehicles, tech services, and healthcare—is concentrated along Haidian’s borders with Shijingshan, Chaoyang, Changping, and the urban core. (2) The Shangdi Cluster in northern Haidian (20.68 km²), spanning Northwest Wang, Wenquan, and Sujiatuo Towns, includes the Shangdi, Yongfeng, and Cuihu Jiedaos and hosts R&D centers of major tech firms such as Baidu’s headquarters and Huawei’s Beijing Research Center. (3) The Zhongguancun Demonstration Zone follows a dual-core structure, with the northern core comprising the Shangdi-Xisanqi, Yongfeng, and Cuihu clusters, while the southern/southeastern core is anchored by the Zhongguancun Original Innovation Cluster. (4) High-tech parks (e.g., Zhongguancun No. 1, IC Design Park, Software Park, Dongsheng Tech Park, and JinYu Smart Factory) and specialized industrial zones (e.g., Shangdong Digital Valley and Digital TV Industrial Park) are situated near Haidian’s boundaries with Changping and Chaoyang. These observations suggest that the primary drivers of job space formation in Haidian are its strong technology sector—concentrated along its periphery with central and neighboring districts—and its metro network (with key hubs such as Shangdi, Zhongguancun, Qinghe, and Xizhimen), which enhances connectivity to Changping, Dongcheng, and Xicheng, facilitating cross-regional industrial collaboration, labor mobility, and commuting flows. Consequently, this job concentration influences housing demand, living costs,

625 and price disparities, resulting in a housing distribution that largely overlaps with employment
626 spaces but covers a more limited area.

627 Second, to assess the job-housing imbalance exacerbated by Haidian's industrial layout, this
628 study quantifies the dominant intensity and spatial patterns of employment-residence functions at
629 the Jiedao and town level using joint measurements of JHB and SD (Fig. 11). Key findings include:
630 (1) Job-dominant areas ($JHB > 1$) exhibit strong spatial agglomeration, primarily in
631 southern/southeastern core zones such as Shangdi and Zhongguancun Jiedaos. This concentrated
632 employment pressure corresponds with Haidian's high-tech industrial clusters but intensifies job-
633 housing imbalances in core areas (higher SD values), reinforcing the link between job-housing
634 dynamics and industrial spatial planning. Industrial agglomeration may also elevate housing prices,
635 rents, and living costs, creating a filtering effect that displaces residential demand outward. (2)

636 Housing-dominant areas ($JHB < 1$) are clustered in northern and southern peripheral zones (e.g.,
637 Shangzhuang and Wenquan Towns). Notably, among the three areas with the highest SD values
638 (Haidian Jiedao, Qinghuayuan Jiedao, and Shangzhuang Town), Shangzhuang exhibits a unique
639 residence-dominated imbalance, contrasting with the employment-dominated imbalance in the other
640 two. As a transitional zone between Haidian and Changping, Shangzhuang serves as a critical
641 residential pressure absorber in the regional job-housing system. Additionally, China's school
642 district policy—which ties school admission to residential location—likely exacerbates housing
643 scarcity and contributes to intensified residential clustering in peripheral areas like Shangzhuang.

644 5.2 Spatiotemporal Evolution of Job-Housing Imbalance at the Jiedao and Town Scale 645 in Haidian District

646 Haidian District is a pivotal region in Beijing's development strategy. Using the redesigned
647 JHSI framework, we analyzed 2023 data, revealing that the spatial distribution of JHB exhibits a
648 compact pattern, whereas SD appears fragmented. To assess the spatiotemporal evolution of job-
649 housing imbalance at the Jiedao and town scale over the past five years, we compare our findings
650 with a similar study by Wang et al. (2020) based on 2018 data. Although the overall JHB pattern
651 remains largely unchanged since 2018, the fragmentation level of SD has increased in 2023. Notably,
652 the value ranges for both JHB and SD in 2023 are significantly narrower than those in 2018,
653 indicating substantial progress in job-housing balance across Haidian District. In 2018, a greater
654 number of Jiedaos and towns—particularly in southern Haidian, adjacent to Beijing's urban core—
655 recorded JHB values exceeding 1.

656 Specifically, in 2018, employment functions were heavily concentrated in Jiedaos such as
657 Zhongguancun (JHB: 3.51–10.51), Shangdi (JHB: 2.51–3.5), and Yongding Road (JHB: 1.51–2.5),
658 where JHB ranges were markedly wider than in surrounding areas. Similarly, SD values highlighted
659 pronounced job-housing separation and elevated pressure in Zhongguancun, Shangdi, Qinghuayuan,
660 Yanyuan, and Haidian Jiedaos. By 2023, however, the overall SD range in Haidian District had
661 contracted, reflecting a reduced concentration of employment functions and a more even distribution
662 across the region. Furthermore, disparities in job and residential functions among Jiedaos and towns
663 have diminished. These improvements signify meaningful advances in mitigating urban land use
664 pressures and enhancing living conditions, aligning with the population and land use targets set forth
665 in the Haidian District Planning (2017–2035). The observed trends confirm that Haidian District's
666 spatial development trajectory is consistent with its planning objectives.

667 5.3 From Methodology to Practice: Policy recommendations for Urban Planning

668 Our redesigned JHSI methodology provides urban planners with an enhanced macro-

669 perspective quantitative tool to address imbalanced job-housing relationships amid rapid
670 urbanization. Using Haidian District as a case study, we examine both the technical scalability and
671 practical applications of this approach to derive policy recommendations.

672 At the technical level, our geospatial big data-driven JHSI-redesigned framework can be
673 further integrated with AI to enable multi-scale regional data iteration and scenario upgrades,
674 ultimately forming an intelligent job-housing interaction platform. For China's territorial planning,
675 a public-private partnership model could effectively bridge internal assessments—such as
676 identifying, evaluating, and optimizing key areas—with broader regional expansion strategies. A
677 notable example is the Beijing Municipal Development and Reform Commission's interactive
678 *Beijing Industrial Layout Map*, which integrates multi-objective industrial patterns with policy
679 guidance for commercial and planning applications. These developments demonstrate that, with
680 further technical refinement, our approach can support decision-making in residential location
681 selection, corporate commercial planning, government transportation infrastructure, and built-
682 environment development through spatially visualized solutions.

683 At the practical level, the method offers multidimensional value. First, it provides a scientific
684 basis for regional industrial restructuring. Within the BTH coordinated development strategy, it
685 enables Haidian District—a high-tech innovation hub—to amplify its impact by fostering a
686 coordinated system where Beijing specializes in R&D while Tianjin and Hebei handle related
687 production activities. Simultaneously, it facilitates the strategic relocation of Beijing's non-capital
688 functions, such as manufacturing, service sectors, and government offices. Spatially visualized job-
689 housing monitoring helps identify industrial clusters for relocation, evaluate spatial pressure on
690 industries targeted for decentralization, and dynamically track balance adjustments. Second, the
691 method can optimize public transit by targeting high-intensity or severely imbalanced job-housing
692 zones through multi-period comparisons, thereby guiding station placement and route planning. For
693 example, congestion in Haidian's Zhongguancun and Shangdi areas could be alleviated by adding
694 subway stations or adjusting bus schedules. Additionally, the approach informs urban renewal
695 projects, such as the redevelopment of older neighborhoods. Third, it can improve the balanced
696 allocation of educational resources. China's school district system exacerbates spatial mismatches
697 between jobs and housing, as concentrated elite schools inflate housing prices and induce long
698 commutes. By embedding educational planning within industrial strategies—supported by our
699 redesigned JHSI tool—these systemic “job spaces-education spaces-housing spaces” conflicts can
700 be mitigated, promoting sustainable urban integration.

701 5.4 Limitations

702 Although the approach redesigned in this study is effective for identifying urban job-housing
703 spaces, three key limitations remain when compared to existing methods based on mobile signaling
704 data. First, a major constraint of our JHSI framework is its inability to capture daily commuting
705 flow information. Given that commuting patterns are crucial for understanding urbanization—as
706 they reflect the spatial distribution and mobility of urban populations—this omission represents a
707 significant drawback, and we cannot conduct further noise reduction for housing base stations.
708 Consequently, our framework can only generate a broad spatial representation of job-housing
709 distributions, which, though useful for macro-level analyses, lacks granularity. Second, the absence
710 of up-to-date census data (due to delays in statistical monitoring) and representative indicators for
711 working and residential populations (including occupational status) hinders further improvements
712 in JHSI accuracy. Third, although age-based filtering of mobile device users has excluded most non-

713 working residents, and our methodology ensures robustness through correlation coefficients and
714 trend analysis, additional data refinement is still needed for two specific groups: (1) working-age
715 non-working individuals (particularly university students), and (2) occupationally mobile
716 populations with irregular residence patterns (e.g., frequent intercity commuters).

717 6 Conclusions

718 This study redesigned a base station-oriented JHSI framework, highlighting the practical utility
719 of LBS data for urban planning applications through urban dynamic monitoring. By replacing
720 individual trajectories with aggregated population clusters and geospatially classified functional
721 station data, we propose a lightweight, efficient, and privacy-preserving JHSI method. Implemented
722 in Haidian District, the approach achieves precision indices of 66% for work identification and 80%
723 for residence identification, demonstrating its effectiveness for urban planning and management—
724 particularly in supporting the objectives of the 2035 Plan (e.g., alleviating housing and population
725 pressures)—while reinforcing Haidian’s pivotal role in China’s BTH coordinated development
726 strategy. Furthermore, we examine its future application potential from both technical platform
727 development and implementation perspectives for urban livability, focusing on: (1) Promoting the
728 optimization of China’s urban territory spatial planning through the rapid monitoring of spatial
729 patterns in job-housing spaces. In particular, it can provide visual insights for adjusting industrial
730 patterns and facilitating regional coordinated development in balancing economic activities,
731 population distribution, and material flows. For instance, it can actively support the periodic and
732 rapid spatial monitoring of Beijing’s non-capital function decentralization under the BTH regional
733 coordinated development strategy, such as monitoring the growth of high-tech industries in Tianjin
734 and Hebei through Haidian’s innovation sector and providing timely adjustment guidance. (2) In
735 terms of transportation planning, efficiently and accurately optimizing station location selection and
736 micro-scale road network design based on population aggregation levels. (3) Indirectly providing
737 visual references for urban patterns to inform social policies related to education and housing. For
738 example, under China’s education system, factors like housing price adjustments and school district
739 housing—which directly affect housing costs and location choices—can exacerbate commuting
740 costs and job-housing separation, and the framework can help illustrate such dynamics.

741 Data availability

742 Dynamic population data used in this study will be made available upon request.

743 Declaration of competing interest

744 The authors declared that they have no conflicts of interest to this work.

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