The agglomeration patterns of different lodging segments around a transportation hub

Bingjie Niu[1], Zhibin Lin[2], Ping Yin[3]*

1. Department of Tourism Management
   Beijing Jiaotong University
   No.3 Shangyuancun, Haidian District, Beijing, 100044
   China
   Email: 18113090@bjtu.edu.cn
2. Durham University Business School
   Mill Hill Lane
   Durham, DH1 3LB
   United Kingdom
   Email: zhibin.lin@durham.ac.uk
3. Department of Tourism Management
   Beijing Jiaotong University
   No.3 Shangyuancun, Haidian District, Beijing, 100044
   China
   Email: pyin@bjtu.edu.cn

* **Corresponding author**: pyin@bjtu.edu.cn

Declarations of interest

None.

The agglomeration patterns of different lodging segments around a transportation hub

Abstract

The main purpose of this paper is to examine how the spatial distribution of the accommodation industry evolved in areas with a high-speed railway (HSR) station. We collected 419 points of interest (POI) data on the accommodation industry within a 3km radius of a high-speed railway station, the Beijingnan HSR Station in Beijing the capital city of China were collected. A range of coefficients and indices such as kernel density, Ripley's K function, nearest neighbor index, and standard deviation ellipse were used as analytical tools The results indicate that the continuous and phased growth in accommodations can be observed in the Beijingnan HSR Station area over the past two decades. The spatial distribution represents a circle agglomeration, and the significant agglomeration happened in the core circle and the periphery circle. Further analysis shows different types of accommodations present diverse agglomeration states. The study has implications for both the research and practice of HSR networks and the development of the accommodation sector.

Keywords: HSR station, accommodation industry, spatial structure, agglomeration, evolution

1. Introduction

As a revolution in the history of transportation, high-speed railway (HSR) networks have created a profound impact on socio-economic development (Ahlfeldt and Feddersen, 2017; Liu et al., 2021), and have consistently received research attention in the tourism and hospitality literature. Accessibility as provided by HSRs, as the main factor boosting opportunities for cities in the network, has been examined and achieved consensus. This was based on the assertion that the value of proximity to accessibility points is capitalized on the value of properties in the station's neighborhood (Debrezion et al., 2007). HSR stations are believed as the first step in a planning process striving to achieve sustainable development for the urban area (Reusser et al., 2008). At the forefront of the cities' communication with other areas, the stations serve as gateways that bring massive flows (of people, logistics, information, and others) to the city, and the neighborhood surrounding the HSRs station is a perfect choice as a new business district, for example, the Lille's 'Euralille' project (Newman and Thornley, 1995; Moulaert et al., 2001), Lyon Part Dieu (Bonnafous, 1987; Mannone, 1997), and Amsterdam Zuid (Trip, 2008; Willigers, 2008). Cities with an HSR station often aim to display a modern image and strive to turn the HSR station into a high-quality urban center (Trip, 2008). Understanding the changes in local spatial structure driven by the HSR stations is critical for both academic research and the urban development of cities with an HSR station.

Previous research has found significant links between HSRs and the value or price of real estate and property (Chen and Haynes, 2015), tourism development (Albalate and Fageda, 2016; Campa et al., 2016; Guirao and Campa, 2016; Kurihara and Wu, 2016; Albalate et al., 2017; Gutiérrez and Ortuño, 2017; Pagliara et al., 2017; Li and Chen, 2019), land-use (Chen et al., 2021), and manufacturing (Sun et al., 2017). Other research related to HSRs has examined the equity problem (Cavallaro et al., 2020), labor market (Zhang, 2021), environmental change (He et al., 2015; Chen et al., 2016; Villalba Sanchis et al., 2020), and innovation activities (Zeng et al., 2021). However, there is little empirical research examining the industrial spatial structure characteristic and changes driven by the HSR stations, even though it has been almost 10 years since the relevant question was raised: whether HSR stations can become the generators of new local poles of urban development in 2013 (Banister and Givoni, 2013).

This study thus aims to address the above research gap by examining the spatial distribution of the accommodation industry in the area surrounding an HSR station, considering the close relationship between travel and accommodation. Specifically, we aim to identify:

a) the characteristics of accommodation spatial distribution in the area surrounding an HSR station;

b) the differences in spatial distributions across the various types of accommodation as influenced by the HSR station; and

c) the changes in the distribution over time since the operation of HSR services.

We choose the Beijingnan HSR Station in Beijing, China as the studying case. This is because the country has over 800 HSR stations, with the longest HSRs operation distances in the world; and Beijingnan station was once a traditional railway station and locates in an urban area, which means it is a typical HSR station transformed from traditional railway stations.

We use Point of Interest (POI) data and other public information on a leading online tourism agency (OTA) website to describe accommodation distribution, and collect all the information within the neighborhood within a radius of 3.0 km from Beijingnan Railway Station. Several indexes such as Ripley's K function, kernel density estimation, nearest neighbor index, and standard deviational ellipse are used to characterize the spatial agglomeration and evolution.

2. Literature review

2.1 HSR station and the distribution of economic activities in its surrounding area

An HSR station is not just a transportation node, but also has the opportunity to play the role of an urban central place (Bertolini, 1999). The construction of an HSR station is first accompanied by a change in land use. The growth rate of land use surrounding the HSR station is usually higher than that of the whole city (Wang et al., 2019). Furthermore, the improved accessibility (Ortega et al., 2012), transport facilities, and modern image (Niu et al., 2021) attract people and businesses to gather in the area, leading to enterprise agglomeration (Eom et al., 2020). Commerce and housing spring up, creating new activities and employment centers (Kamga, 2015). These make the neighborhood more accessible, and further boost economic activities (Chatman and Noland, 2014). However, the catalytic effect of HSR stations on urban development is not always effective. European cases show that HSR stations do play a role in promoting urban development in first-and second-tier cities, while do not bring any catalysis in other cities (Loukaitou-Sideris et al., 2012). Similar cases can be observed in China. The HSR station in Huangzhou has a significant impact on the value of nearby residential properties, while the HSR station in Guangzhou has no significant influence on economic activities in its surrounding area (Diao et al., 2017).

Some researchers speculate that the different influences might be determined by geographical spatial ranges (Debrezion et al., 2007; Geng et al., 2015), and the vitality of urban activities surrounding the station may be dependent on the spatial context around it (Kim et al., 2018). The ‘node-place’ model can be used to understand the balanced development process in the station area (Chorus and Bertolini, 2011), and the development zones surrounding an HSR station can be categorized as primary, secondary, and tertiary zones (Schütz, 1998). The basic and derivative service industries are mainly concentrated in the primary and secondary zones, while the related service industries are mainly distributed in the secondary and tertiary zones (Wang et al., 2021). While the impact of an HSR station on the location choice of enterprises in the station area has been well recognized (Beckerich et al., 2017), there is currently little research on the spatiotemporal structure evolution of the economic activities in the HSR station areas, particularly the accommodation industry.

2.2 HSR station and the development of the accommodation industry

The accommodation industry, aka lodging industry, is important content in traveling industry, and is also an important part in the urban economics. Therefore, the evolution discipline of the location selection and spatial structure of the hotel industry have become the traditional and hot topics of academic research, which can be classified as a component of geography of tourism (Van Doren and Gustke, 1982).

Traffic conditions are always important factor discussed in the location selection of hotels. Except of traffic convivence, specific considerations for hotels' location selection are claims as local economic environment, regional or zone regulations, height limit of buildings, car park facilities, public facilities, geographic factors, natural resources, the size of the location(Gray and Liguori, 1998), fine visual perception, public facilities and other services, application of certain regulations, and flexible space by Pan (2002) and political factors (Shoval and Cohen-Hattab, 2001). Chou et al.(2008) presented a fuzzy multi-criteria decision making model for hotel location selection, which has 21 criteria. Traffic condition, as one of the four perspectives, is complained as two factors (access and convenience) and 7 criteria. In recent research, road accessibility, transportation facilities, public service infrastructure, land use types, urban population, attractions are all important determinants(Yang et al., 2012; Li et al., 2015).

Concepts in location theory can explain why traffic and transportation are so important to hotel industry. Two key concepts in central place theory, service scope and demand threshold, are basic operation principle for hotel. Spots with convenient traffic and transportation can bring customers from specific distance to the hotel to ensure minimum consumer number.

What spots are the fine locations for hotels? Empirical research and modelling work tried to find the answer. Research before Ritter (1986)find that location of historical core and most of the attractions. Data from the U.S. department of Commerce Census of Business in 1963, 1972, and 1977 were compared to analyze the spatial growth points of the U.S. lodging industry (Van Doren and Gustke, 1982). The results point to major lodging growth areas in the Sunbelt states with central Florida, Las Vegas, Nevada and Hawaii as outstanding nodes of development. Arbel and Pizam (1977), Wall et al.(1985), and Hofmayer (1986) demonstrated that hotels prefer to locate near the city center, which is the heart of circular model of land use proposed by Yokeno (1968). While, as maker and breaker of cities, transportation technology changes things. Ritter (1986)proposed a model based on the study of the distribution of Nureberg's hotels to explain the spatial structure of hotel industry, and the model claims for the first time that hotels tend to be concentrated close to the train station after the introduction of railways. The fast train era led to an increase in the importance of hotel districts close to railway stations. Not only cities connected to the HSR network have seen significant growth in employment in the accommodation industry (Dong, 2018), but also higher frequency HSR service systems or HSR stations generally have higher hotel occupancy rates (Deng et al., 2020). Empirical evidence suggests that the opening of the HSR has promoted industrial clustering in the accommodation industry in the Guangdong-Hong Kong-Macau Greater Bay Area (Fang et al., 2020) as well. Being the perfect location for hotel industry with the most convenient traffic condition, we have enough theoretical evidence to believe that fast train station witnesses the boost of hotel industry, and this paper will demonstrate this hypothesis with empirical research based on data collected from Beijingnan HSR station.

In fact, early back to 2001, Shoval and Cohen-Hattab criticized that ed that Ritter ignored the type of hotels. In recent decades, star rating, or we can say, the type of hotels has come into research's attention. Lei and Lam (2015) found that star rating has a negative impact on the hotel performance. The relationship between the degree of agglomeration and hotel type (usually can be described as the cost) is an inverted 'U'-shape (Marco-Lajara et al., 2014). The agglomeration effect is heterogeneous for different types of hotels (Yang et al., 2014), and lower-end hotels are more likely to receive positive spillover effects by co-locating in a cluster with upscale hotels (Canina et al., 2005), which can be seen the same distribution pattern from Airbnb (Gutiérrez et al., 2017).

When studying different types of hotels' distribution character from transportation perspectives, two opposite opinions exist. One view is that upscale hotels tend to be located in transportation hubs, as well as urban centers, key scenic spots and peripheral new cities(Li et al., 2020). The other is that transportation hubs, take HSR station as example, can only affect budget hotels' distribution not luxury hotels(Deng et al., 2020). Being one of the most important transportation hubs, what characters will be shown when different types of hotels distribute in HSR stations needs more empirical study. Beijingnan HSR station will be took as the case to illustrate four types of hotels' distribution characters and changes along with fast trains operation.

3. Methodology

3.1 Beijingnan HSR Station, Beijing

Beijingnan HSR Station locates in Fengtai District, Beijing, and was founded in 1897, when it was called Majiabu Station and served railway lines connecting Beijing and cities south of Beijing. The transformation of the station into an HSR station started in 2006, and was completed and opened for service in 2008 with the operation of the Beijing-Tianjin Intercity High-Speed Rail Service. Beijingnan HSR station is the first large-scale comprehensive transportation hub in China, which integrates HSRs with other public transport services such as regular trains, subways, buses, and taxis. The HSR Station now has four tracks and 13 platforms covering an area of 32 hectares, and has become a landmark in Beijing. Fig. 1 shows the pictures of Beijingnan Station before and after its transformation into an HSR station.

Fig. 1. Beijingnan HSR Station (Source: http://blog.sina.com.cn/s/blog_45d4d1900100s1ni.html and https://linyi.tuchong.com/17037544/)

As a specific regional concept in urban spatial structure, HSR station area has not been universally defined, but its character and function have been widely acknowledged (Ribalaygua and Perez-Del-Caño, 2019). In this study, we define the HSR station area as an area that has been developed and centered with the construction of an HSR station. Based on the literature (Sorensen, 2000; Wang et al., 2019), we took 3.0 km as the maximum radius as the boundary of the HSR station area which is the average acceptable distance for passengers to travel by car (Wang et al., 2012). We divided the area within the radius of 3.0 km surrounding the Beijingnan HSR Station by 500 m into six circles, to observe the distribution characteristics of the accommodation industry.

3.2 Data collection

This study takes Amap LBS Service (https://lbs.amap.com/) as the basic data source. According to the POI classification of the platform, we use “accommodation service” as the keyword to obtain the overall POI data of the accommodation industry in Beijing in September 2021. POI refers to a geographical entity that is closely related to socio-economic activities, and can be described by commercial facilities, bus stations, high buildings, and so on in Geographical Information System (Lu et al., 2020). POI is inextricably linked to modern (mobile) search, recommender systems, location-based social networks, transportation studies, navigation and tourism systems, urban planning, predictive geo-analytics such as crime forecasting, and so forth (McKenzie et al., 2015). Compared with traditional data, POI data has the advantages of a large sample size and easy access, and it can reveal the distribution of the industry in the station area on the micro-scale more effectively and comprehensively.

Arcgis 10.2 is used to spatialize the data and extract data by taking Beijingnan HSR Station as the center and 3.0 km as the radius. A total of 453 items of accommodation information in the station area are obtained initially.

The types of accommodation were classified into four categories based on previous studies (Leung et al., 2018; Yi et al., 2021), matching the classification of hotels on the key online travel platforms, including Meituan, Ctrip and TripAdvisor: Ordinary accommodation includes inns and guesthouses; Shared accommodation includes day rentals and homestays; Economy accommodation includes economic chain hotels, and two-star and below hotels; Three-star and above hotels and those hotels not star-rated but labeled as luxurious are classified as Quality accommodation.

With the help of Meituan, Ctrip, Tongcheng-Elong and other OTA websites, all accommodation enterprises are double-checked one by one, matching the opening date and grade type information. After the whole data checking and cleaning, including removing hotels that opened after 2020, a total of 419 accommodation enterprises' POIs in the area of Beijingnan HSR Station were retained, including the enterprise's name, geographical location, opening date, and type. In order to ensure the accuracy of the data, five accommodation enterprises were randomly selected from each category and the authors went for a field investigation to make sure all the information are correct. After verifying that the actual situation is consistent with the data collected, the POI database of the accommodation industry in Beijingnan Railway Station is constructed (Fig. 2).

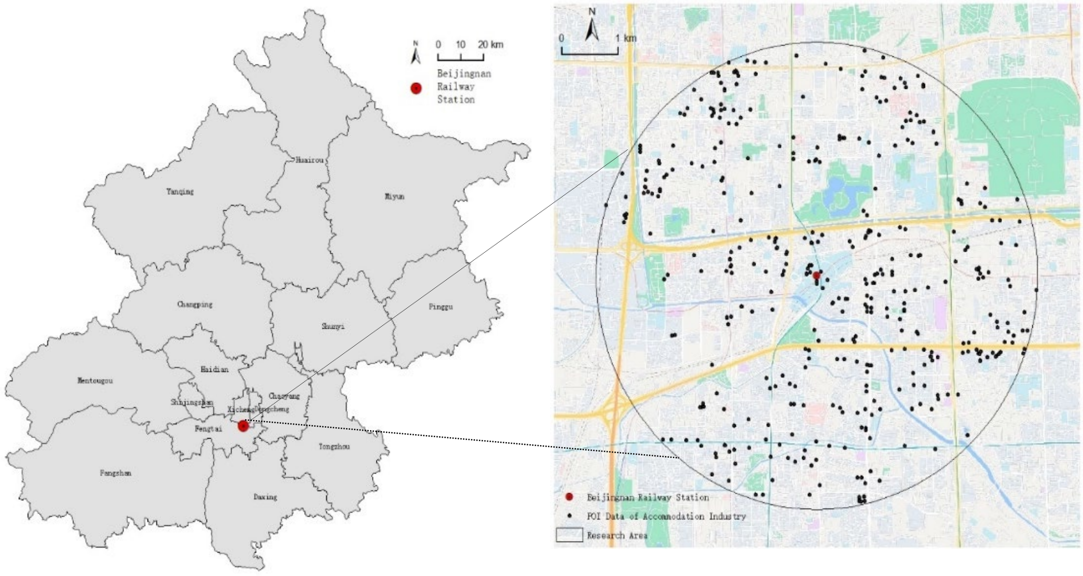


Fig. 2. POIs of accommodation in Beijingnan HSR Station Area

3.3 Measures of the accommodation spatial distribution

In this study, we use four indexes to analyze the spatial distribution and evolution characteristics of the accommodation industry in the HSR station area from different perspectives. Kernel density estimation (KDE) reflects the relative concentration degree of points distribution in the station area, and Ripley's K function can show the agglomeration state of the accommodation industry at different distance scales. They are the overall spatial structure characteristics. Nearest neighbor index (NNI) and standard deviational ellipse (SDE) are chosen to measure the evolution process of the accommodation industry in the station area, which can help us to understand the regularity of dynamic change.

3.3.1 Kernel density estimation

KDE is a nonparametric spatial analysis method (Xie and Yan, 2008; Zhu et al., 2017), which is widely used in the spatial agglomeration analysis of point data. The method is mathematically represented as follows:

$$f(X) = \frac{1}{nh^d} \Sigma_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (1)$$

Where $f(X)$ refers to the KDE, n is the number of accommodation enterprises, $d$is the dimension, K represents the spatial weight, and h is the threshold value of distance attenuation, that is, bandwidth. Generally, the farther away from the event x_i, the smaller the spatial weight. $(x - x_i)$ represents the distance from the estimated point x to the event x_i.

3.3.2 Ripley's K function

Spatial distance is a critical parameter to describe the distribution characteristics of spatial elements. Based on different spatial distances, spatial elements usually act out different agglomeration patterns (Gao and Jin, 2015). Ripley's K function is an analysis function for calculating cumulative distribution, which can be used to explore the agglomeration and diffusion of point elements at different distances. It has the advantages of accuracy, simplicity, and ease of use. Furthermore, it is suitable for multi-scale spatial pattern analysis (Okabe and Yamada, 2001), and is widely used in small-scale studies as well (Jung and Jang, 2019).

The common transformation of the K function, also known as $L(d)$ is:

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1}^{n} k_{(i,j)}}{\pi n(n-1)}}, \quad (i \neq j) \quad (2)$$

where, d is the distance, A represents the acreage of the research area, n represents the number of research elements, and $k_{(i,j)}$ is the factor's weight. When the distance between point i and point j is less than d, the weight is 1. Otherwise, it is 0. Five parameters are returned after being calculated with ArcGIS 10.2: Observed K, Expected K, Diff K(difference between the first two parameters), the highest confidence interval (Hi Conf Env), and the lowest confidence interval (Lw Conf Env). Diff K > 0 indicates that the spatial clustering degree of the distance is higher than that of the random distribution of the distance. Otherwise, it indicates that the dispersion degree of the distribution is higher. Diff K means the corresponding distance has the strongest spatial clustering significance. Confidence intervals are used to measure whether spatial clustering or dispersion has statistical significance.

3.3.3 Nearest neighbor index

NNI is used to analyze the agglomeration and dispersion of economic activities. Wang et al. (2014) analyzed the agglomeration and dispersion of various retail stores in Changchun based on NNI from the perspective of street centrality. Based on the average nearest neighbor tool in ArcGIS 10.2, this paper first calculated the distance between each factor of interest and its nearest factor, and then calculated the average value of all the nearest neighbor distances. $NNI < 1$ means the pattern is clustering, otherwise, the pattern tends to diffuse. The expression is:

$$NNI = \overline{D_o}/\overline{D_E} \tag{3}$$

$$\overline{D_0} = \sum_{i=1}^{n} \frac{min(d_{ij})}{n} \tag{4}$$

$$\overline{D_E} = \frac{1}{2}\sqrt{\frac{A}{n}} \tag{5}$$

Where, $\overline{D_0}$ is the actual mean nearest neighbor distance between factor points, $\overline{D_E}$ is the ideal average distance between POI points in accommodation, i and j are arbitrary two POI points, A is the regional area, and n is the number of elements.

3.3.4 Standard deviational ellipse

SDE is an algorithm that analyzes the direction and distribution of point elements. It can describe quantificationally the spatial distribution situation and evolution characteristics of the research objects through the spatial distribution ellipse with the center point, azimuth, long semi-axis and short semi-axis as the basic parameters (Lefever, 1926). Shi et al. (2021) analyzed the spatial attributes of Meituan take-away from the business district perspective by using SDE. The center point of the ellipse represents the relative position of the spatial distribution of the elements, the long semiaxis represents the distribution direction of data, the short semiaxis represents the distribution range, and the azimuth represents the angle formed by clockwise rotation from due north to the long semiaxis of the ellipse. The larger the difference between the values of the long and short semiaxes, the larger the flattening, and the more obvious the directivity of the data. The calculation formula is as follows:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{X})^2}{n}} \tag{6}$$

$$SDE_y = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{Y})^2}{n}} \tag{7}$$

where x_i and y_i are the coordinates of element i, $\{\bar{X},\bar{Y}\}$represents the average center of elements, and n is the total number of elements.

The calculation method of rotation angle is as follows:

$$\tan\theta = \frac{A+B}{C} \tag{8}$$

$$A = \left(\sum_{i=1}^{n}\tilde{x}_i^{\,2} - \sum_{i=1}^{n}\tilde{y}_i^{\,2}\right) \tag{9}$$

$$B = \sqrt{\left(\sum_{i=1}^{n}\tilde{x}_i^{\,2} - \sum_{i=1}^{n}\tilde{y}_i^{\,2}\right)^2 + 4\left(\sum_{i=1}^{n}\tilde{x}_i\,\tilde{y}_i\right)^2} \tag{10}$$

$$C = 2\sum_{i=1}^{n}\tilde{x}_i\tilde{y}_i \tag{11}$$

$\tilde{x}_i$ and $\tilde{y}_i$ are the difference between the mean center and the xy coordinates.

The standard deviation of the x-axis and y-axis is:

$$\sigma_x = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}(\tilde{x}_i \cos\theta - \tilde{y}_i \sin\theta)^2}{n}} \qquad (12)$$

$$\sigma_y = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}(\tilde{x}_i \sin\theta - \tilde{y}_i \cos\theta)^2}{n}} \qquad (13)$$

4. Results

4.1 Overall quantitative characteristics and changes over time

Fig.3. shows the changes in the size of the accommodation enterprises across the four categories from 2001 to 2020.

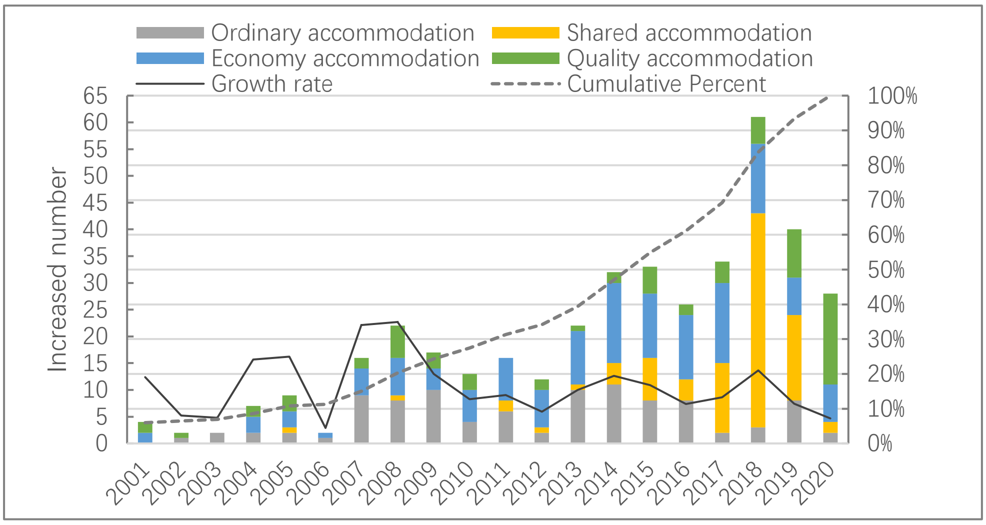


Fig. 3. Statistics of accommodation industry in the study area (2001-2020)

The accommodation industry shows continuous growth from 2001 to 2020, which we can get from the fact that there are newly opened enterprises in the area each year, even in 2006, the year when Beijingnan Railway Station was closed for renovation. While it is not average but phased growth during the study period. The growth rate over the past 20 years shows that the growth reached its stage peak in 2005, 2008, 2011, 2015, and 2018 respectively, with the highest growth rate of 35% in 2008. The lowest growth rate is in 2006. From the overall trend, the growth rate in the first decade is higher than in the second decade.

The growth trends over time vary across the types of accommodation enterprises. Quality accommodations show continual growth, especially after 2016; Shared accommodations have significant growth in the later decade, while there was not much growth in the first decade; Economy and Ordinary accommodations show a similar trend of growth, with growth rates increasing first and decreasing later. However, the peaks are different: Economy accommodations have a continual growth peak in 2014-2018, while ordinary accommodations have a peak in 2007-2009 and 2013-2016.

4.2 Spatial characteristic analysis

4.2.1 Circle structure analysis

KDE method in ArcGIS10.2 was used to conduct spatial analysis on POI data of the accommodation industry in Beijingnan HSR station area, and the results are shown in Fig. 4

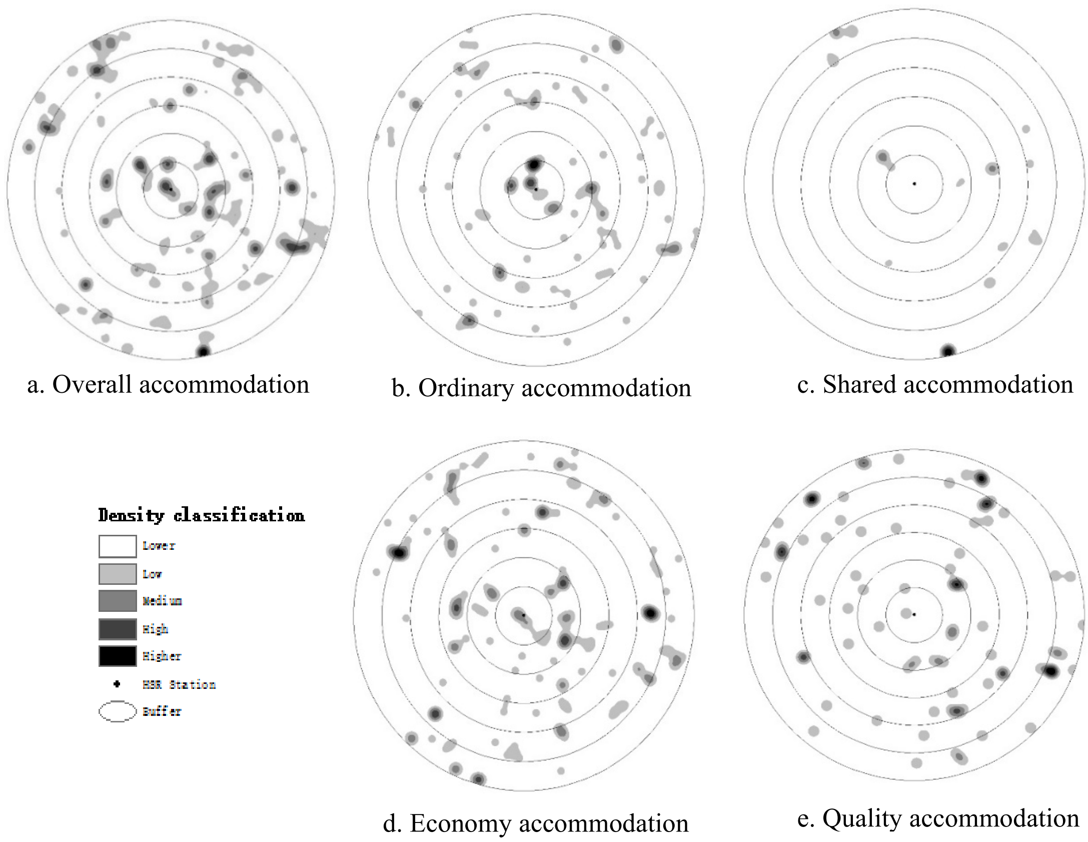


Fig. 4. Accommodation kernel density estimation

The overall spatial distribution has three characteristics, which can be observed in Fig.4 (a). First, circles of 0-1000m and 2000-3000m have a higher density than the circle of 1000-2000m. Secondly, the density of the northwest-southeast diagonal is higher than that of the northeast-southwest diagonal. Finally, the west of the station has the lowest density in the whole picture.

The distribution characteristics vary across the different types. Fig.4 (b) shows the Ordinary accommodations spatial distribution, the highest density appears in the circle of 0-500m, and several agglomeration points are relatively evenly distributed in other circles. Shared accommodation has a unique and obvious characteristic in spatial distribution, that is, there are only a few aggregation points in a limited number of places, and the density in other places is quite low (Fig. 4c). Economy accommodation's distribution characteristic can be described as coexisting of evenly distributed and relatively concentrated (Fig. 4d). We can find medium and over medium density spots in every circle, and higher density in several spots. Quality accommodation in each circle has a gathering performance, but the highest density is mainly in the 2~3 km circle (Fig. 4e).

When examining the characteristics of different circles, we found that the distribution of ordinary accommodation is more concentrated in the circle of 0-500m, economy accommodations tend to locate in the circle of 500-1000m, and quality accommodation is found to agglomerate in the circle of 2000-3000m.

4.2.2 Distance pattern analysis

The multi-distance spatial clustering analysis tool of the spatial classification model based on Ripley's K in ArcGIS10.2 was used to further explore the distance relationship and distribution pattern of the accommodation industry in the HSR station area on a certain spatial scale. The initial distance is set at 0 and the incremental distance is set at 100 meters. After 30 iterations, the observed values of the overall and four types of accommodation at different distance scales are analyzed. The analysis results can be interpreted as: the observed values of the analysis objectives are greater than the high value of the confidence interval within a certain distance, and its aggregation distribution statistics have good significance; and the intersection of the observed value curve and the expected value curve indicates that there is aggregation differentiation within this distance. The larger the difference between the observation distance and the expected distance, it indicates the degree of aggregation is the most significant. The results are shown in Fig. 5.

We notice that the observed values of the whole and various types of accommodation industry are greater than the high value of the confidence interval within a certain distance, and its aggregation distribution statistics are significant. Observing the intersection of the observed value curve and expected value curve, we found that: the overall accommodation industry is clustered within the distance scale of 1700m, and dispersed over 1700m; Ordinary accommodations are aggregated within 1600m, and dispersed in the distance longer than 1600m; Shared accommodations are clustered within 1400m, and dispersed when it is longer than 1400m; Economic accommodations are clustered within 1200m, and dispersed in longer than 1200m; Quality accommodations are clustered within 900m, and dispersed above 900m.

Fig. 5 further illustrates that the best aggregation distances of various types of accommodation industry are 700m for overall accommodation, 400m for ordinary accommodation, 100m for shared accommodation, 300m for economic accommodation, and 200m for quality accommodation. We can see that the best gathering distance for the accommodation industry in the HSR station area is within 1km. The four different types of accommodation industry show a certain aggregation state in spatial distribution, the best agglomeration distance is within 500m, and the maximum agglomeration scale is within 2km.

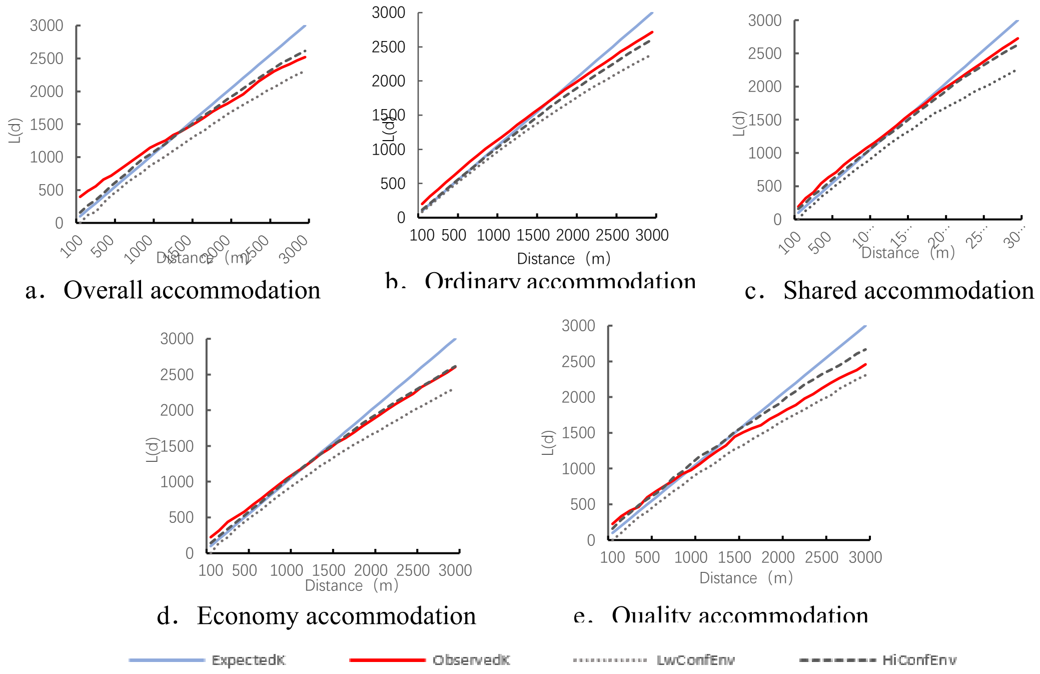


Fig. 5. Multi-distance spatial clustering

4.3 Temporal evolution characteristics

4.3.1 Evolution of agglomeration characteristic

The nearest neighbor index analysis tool of ArcGIS10.2 was used to explore the spatial agglomeration of accommodation enterprises in the HSR station area in different years, and the results are shown in Table 1.

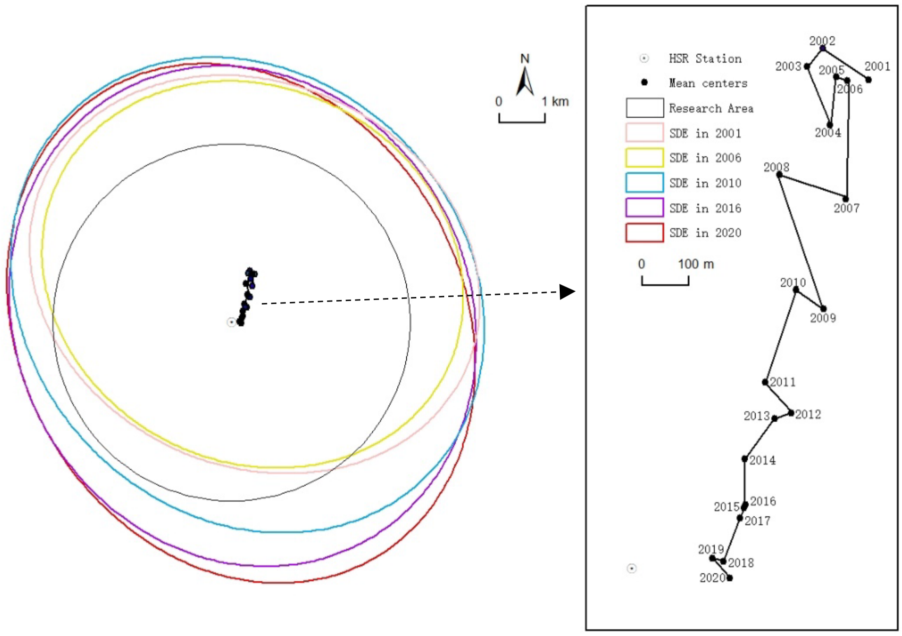
Table 1. The nearest neighbor index results in 2001-2020

Time	NNI	p	Time	NNI	p
2001	1.171	0.102	2011	0.863	0.003
2002	1.216	0.031	2012	0.830	0.000
2003	1.115	0.236	2013	0.794	0.000
2004	0.998	0.975	2014	0.753	0.000
2005	0.909	0.240	2015	0.742	0.000
2006	0.901	0.193	2016	0.732	0.000
2007	0.918	0.215	2017	0.704	0.000
2008	0.835	0.003	2018	0.703	0.000
2009	0.827	0.000	2019	0.683	0.000
2010	0.839	0.000	2020	0.685	0.000

Accommodation industry in the study area is random in 2001-2007, because NNI is bigger than 1 in 2001-2003, and even NNI is smaller than 1 but P value did not pass the significance test; and NNI is smaller from 2008 and continual smaller over the time, which means that the accommodation in Beijingnan HSR station area started agglomeration from 2008, and the level of agglomeration level is higher and higher.

4.3.2 Evolution of spatial distribution center

SDE analysis results, which are shown in Fig. 6, describe the evolution of the accommodation industry spatial distribution over time. First, the distribution presents a ‘Northwest-Southeast’ pattern, and the range is expanding year by year from 2001 to 2020. Secondly, the mean center moving track, which is displayed in the right part of Fig.6, shows a moving direction from Northeast to Southwest, and keeping closer and moving faster to the station.



5. Discussion and conclusion

Taking the Beijingnan HSR Station area as a studying case, this study reveals the spatial distribution and temporal evolution characteristics of the accommodation industry in an HSR station area based on KDE, Ripley' K function, NNI, and SDE by using the POI data of the accommodation industry. The results show that the accommodation industry in the HSR station presents the spatial characteristics of circle distribution and temporal evolution discipline. Furthermore, there are diverse growing trends and different clustering distances across different accommodation types.

5.1 Study contributions

The study reveals the phrased growth characteristic of the accommodation industry in the Beijingnan station area and several peaks are 2008, 2011, 2015, and 2018. The results confirm the periodic view of the impact of HSR on urban economic growth (Huang and Xu, 2021). Another peak appeared in 2005, which is earlier than the operation of HSR, supporting the findings by (Huang and Du, 2020) that the spillover effects of HSR on developed cities start to appear even during the construction period. The highest growth rate of 35% happened in 2008 which is the exact year of Jingjin HSR operation, which shows that HSRs will first promote the development of tourism and service industries (Masson and Petiot, 2009; Pagliara et al., 2017). We also found that quality accommodation has the most significant growth in Beijingnan HSR station, indicating that high quality and high profitable activities will be located around HSRs stations, and HSR stations would be the generators of the cities (Wenner and Thierstein, 2021).

In this study, we found that the spatial distribution of the accommodation industry in the HSR station area represents a circle agglomeration, with the most significant agglomeration in the core circle (0-1000 m) and the periphery circle (2000-3000 m), which enriches the research on the spatial layout of HSR station area. In contrast, previous studies show that gathering spots appear in the range of 5km around the HSR station (Eom et al., 2020), and the changes in land use by HSR are concentrated within 2km from the stations (Wang et al., 2019).

This study examines different types of accommodations' spatial distribution characteristics. Different types of accommodation facilities in HSR stations present diverse agglomeration states at different distances, but the whole variant trend is identical. The best agglomeration distance of the four types of accommodation is within 500m, and the maximum agglomeration scale is within 2km. We found that the higher class the accommodation is, the shorter the distance and the smaller the scale of maximum agglomeration is. The conclusion shows the same rule in the catering industry (Jung and Jang, 2019).

The characteristics of the spatial distribution vary across the different types of accommodations. Budget hotels tend to choose converted buildings located on the edge of the city center (Nield et al., 2014) and places close to high-quality hotels (Huang et al., 2014). The improvement of accommodation standards increases the proportion of high star rating hotels in new hotels (Rogerson, 2013). The concentration of shared accommodation has accelerated the "Gentrification" of the region (La et al., 2021), which will further squeeze the market for ordinary accommodation.

The accommodation industry in the Beijingnan HSR station area started to gather after the opening of the station. The degree of agglomeration was continuously strengthened, and the distribution center moved closer to the station year by year. Previous studies suggest that the location choice of new enterprises is affected by the agglomeration economy and HSR accessibility (Chang and Zheng, 2022), and the agglomeration effect varies with industrial types and geographical conditions. The accommodation industry has higher labor productivity in the area with stronger TOD characteristics (Lyu et al., 2020). The longer the opening time of the HSR station, the better the infrastructure construction of the station area, and the more complete the industrial functions. After the formation of the high-speed rail urban sub-center, the urban center is no longer the only ideal area for the spatial layout of the hotel industry due to the polycentric development of the hotel industry (Li et al., 2020). The location advantages of the high-speed railway station area attract the influx of the accommodation industry, and gradually form a mature agglomeration economy.

5.2 Implications for practice

The basic conclusions of spatial distribution characteristics and temporal evolution of the accommodation industry in the HSR station area obtained in this paper can be further applied to the layout planning and construction of the HSR station. The conclusions can be used to guide the rational planning and development of land in the area around the HSR stations and optimize the allocation of accommodations. Governments are committed to setting up high-end business districts in the region. The introduction of high-quality projects such as high-star hotels can help to bring more activities to the HSR station area. For example, St. Pancras International Station was opened during the 2012 London Olympic Games. There are five-star hotels in the station area and has become a public art and activity place (Kamga, 2015). Changsha South Railway Station area in China has become a large urban complex, and one five-star hotel and five other hotels have the station as a ‘star hotel cluster’. Furthermore, city planners and accommodation enterprises should pay more attention to the circle distribution disciplines for different types of accommodations, and choose the ‘perfect’ locations for the newly opened enterprises.

5.3 Limitations and future research

This study analyzes the agglomeration characteristics of the accommodation industry in a specific HSR station located in the center of a large metropolitan city, the findings cannot be generalized to all types of HSR stations. Future research will advance the field by delving into the mechanism of the effect of HSR stations and the evolution of the accommodation industry’s spatial structure by examining the influencing factors (e.g., urban energy level, HSR station node-place value) on the differentiation characteristics of the spatial structure of the accommodation industry in different types of HSR stations.

References

Ahlfeldt, G.M., Feddersen, A., 2017. From periphery to core: Measuring agglomeration effects using high-speed rail. J Econ Geogr 18, 1-36.

Albalate, D., Campos, J., Jiménez, J.L., 2017. Tourism and high speed rail in Spain: Does the AVE increase local visitors? Ann Tourism Res 65, 71-82.

Albalate, D., Fageda, X., 2016. High speed rail and tourism: Empirical evidence from Spain. Transportation Research Part A 85, 174-185.

Arbel, A., Pizam, A., 1977. Some determinants of urban hotel location: the tourists’ inclinations. Journal of Travel Research 15, 18-22.

Banister, D., Givoni, M., 2013. High-Speed Rail in the EU27: Trends, Time, Accessibility and Principles. Built Environment 39, 324-338. https://doi.org/https://doi.org/10.2148/benv.39.3.324

Beckerich, C., Benoit-Bazin, S., Delaplace, M., 2017. Does High Speed Rail Affect the Behaviour of Firms Located in Districts around Central Stations? The Results of Two Surveys Conducted in Reims in 2008 and 2014. Transportation Research Procedia 25, 3017-3034. https://doi.org/10.1016/j.trpro.2017.05.287

Bertolini, L., 1999. Spatial Development Patterns and Public Transport: The Application of an Analytical Model in the Netherlands. Planning Practice and Research 14, 199-210.

Bonnafous, A., 1987. The regional impact of the TGV. Transportation 14, 127-137. https://doi.org/10.1007/BF00837589

Campa, J.L., López-Lambas, M.E., Guirao, B., 2016. High speed rail effects on tourism: Spanish empirical evidence derived from China's modelling experience. J Transp Geogr 57, 44-54. https://doi.org/10.1016/j.jtrangeo.2016.09.012

Canina, L., Enz, C.A., Harrison, J.S., 2005. Agglomeration effects and strategic orientations: Evidence from the U.S. lodging industry. Acad Manage J 48, 565-581.

Cavallaro, F., Bruzzone, F., Nocera, S., 2020. Spatial and social equity implications for High-Speed Railway lines in Northern Italy. Transportation Research Part A: Policy and Practice 135, 327-340. https://doi.org/10.1016/j.tra.2020.03.028

Chang, Z., Zheng, L., 2022. High-speed rail and the spatial pattern of new firm births: Evidence from China. Transportation Research Part A: Policy and Practice 155, 373-386. https://doi.org/10.1016/j.tra.2021.11.020

Chatman, D.G., Noland, R.B., 2014. Transit Service, Physical Agglomeration and Productivity in US Metropolitan Areas. Urban Stud 51, 917-937.

Chen, Z., Haynes, K.E., 2015. Impact of high speed rail on housing values: an observation from the Beijing–Shanghai line. J Transp Geogr 43, 91-100. https://doi.org/10.1016/j.jtrangeo.2015.01.012

Chen, Z., Xue, J., Rose, A.Z., Haynes, K.E., 2016. The impact of high-speed rail investment on economic and environmental change in China: A dynamic CGE analysis. Transportation Research Part A: Policy and Practice 92, 232-245. https://doi.org/10.1016/j.tra.2016.08.006

Chen, Z., Zhou, Y., Haynes, K.E., 2021. Change in land use structure in urban China: Does the development of high-speed rail make a difference. Land Use Policy 111, 104962. https://doi.org/10.1016/j.landusepol.2020.104962

Chorus, P., Bertolini, L., 2011. An application of the node-place model to explore the spatial development dynamics of station areas in Tokyo. J Transp Land Use 4, 45-58.

Chou, T., Hsu, C., Chen, M., 2008. A fuzzy multi-criteria decision model for international tourist hotels location selection. Int J Hosp Manag 27, 293-301. https://doi.org/10.1016/j.ijhm.2007.07.029

Debrezion, G., Pels, E., Rietveld, P., 2007. The Impact of Railway Stations on Residential and Commercial Property Value: A Meta-analysis. J Real Estate Financ 35, 161-180. https://doi.org/10.1007/s11146-007-9032-z

Deng, T., Gan, C., Hu, Y., 2020. Do hotel business benefit from increased tourist accessibility? Evidence from China ' s high-speed railway program. Tourism Econ 27, 1357-1374. https://doi.org/10.1177/1354816620923216

Diao, M., Zhu, Y., Zhu, J., 2017. Intra-city access to inter-city transport nodes: The implications of high-speed-rail station locations for the urban development of Chinese cities. Urban Stud 54, 2249-2267. https://doi.org/10.1177/0042098016646686

Dong, X., 2018. High-speed railway and urban sectoral employment in China. Transportation Research Part A: Policy and Practice 116, 603-621. https://doi.org/10.1016/j.tra.2018.07.010

Eom, J.K., Lee, K., Song, J.Y., Lee, J., 2020. Analysis of Mobile Phone Data to Compare Mobility Flows and Hotspots Before and After the Opening of High-Speed Railway: Case Study of Honam KTX in Korea. Applied Sciences 10, 5009. https://doi.org/10.3390/app10145009

Fang, L., Zhang, X., Feng, Z., Cao, C., 2020. Effects of High-speed Rail Construction on the Evolution of Industrial Agglomeration: Evidence from Three Great Bay Areas in China. E+M Ekonomie a Management 23, 17-32. https://doi.org/10.15240/tul/001/2020-2-002

Gao, C., Jin, F., 2015. Spatial pattern and industrial characteristics of economic technological development areas in eastern coastal China. Acta Geographica Sinica 70, 202-213. https://doi.org/10.11821/dlxb201502003

Geng, B., Bao, H., Liang, Y., 2015. A study of the effect of a high-speed rail station on spatial variations in housing price based on the hedonic model. Habitat Int 49, 333-339. https://doi.org/10.1016/j.habitatint.2015.06.005

Gray, W.S., Liguori, S.C., 1998. Hotel and motel management and operations, third ed. Prentice-Hall, Englewood Cliffs,NJ.

Guirao, B., Campa, J.L., 2016. Cross Effects between High Speed Rail Lines and Tourism: Looking for Empirical Evidence Using the Spanish Case Study. Transportation Research Procedia 14, 392-401. https://doi.org/10.1016/j.trpro.2016.05.091

Gutiérrez, A., Ortuño, A., 2017. High speed rail and coastal tourism: Identifying passenger profiles and travel behaviour. Plos One 12, e179682. https://doi.org/10.1371/journal.pone.0179682

Gutiérrez, J., García-Palomares, J.C., Romanillos, G., Salas-Olmedo, M.H., 2017. The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. Tourism Manage 62, 278-291. https://doi.org/10.1016/j.tourman.2017.05.003

He, G., Mol, A.P.J., Zhang, L., Lu, Y., 2015. Environmental risks of high-speed railway in China: Public participation, perception and trust. Environ Dev 14, 37-52. https://doi.org/10.1016/j.envdev.2015.02.002

Hofmayer, A., 1986. Some Geographical Aspects of Tourism in Vienna, In Vetter, F. (Ed.), Big City Tourism, Reimer,Berlin, pp. 200-212.

Huang, S., Liu, Z., Hsu, C., 2014. Customer Experiences with Economy Hotels in China: Evidence from Mystery Guests. Journal of Hospitality Marketing and Management 23, 266-293.

Huang, Y., Xu, W.A., 2021. Spatial and temporal heterogeneity of the impact of high-speed railway on urban economy: Empirical study of Chinese cities. J Transp Geogr 91, 102972. https://doi.org/10.1016/j.jtrangeo.2021.102972

Huang, Z., Du, X., 2020. How does high-speed rail affect land value? Evidence from China. Land Use Policy 101, 105068.

Jung, S.S., Jang, S.S., 2019. To cluster or not to cluster?: Understanding geographic clustering by restaurant segment. Int J Hosp Manag 77, 448-457. https://doi.org/10.1016/j.ijhm.2018.08.008

Kamga, C., 2015. Emerging travel trends, high-speed rail, and the public reinvention of U.S. transportation. Transport Policy 37, 111-120. https://doi.org/10.1016/j.tranpol.2014.10.012

Kim, H., Sultana, S., Weber, J., 2018. A geographic assessment of the economic development impact of Korean high-speed rail stations. Transport Policy 66, 127-137. https://doi.org/10.1016/j.tranpol.2018.02.008

Kurihara, T., Wu, L., 2016. The Impact of High Speed Rail on Tourism Development: A Case Study of Japan. The Open Transportation Journal 10, 35-44. https://doi.org/10.2174/1874447801610010035

La, L., Xu, F., Hu, M., Xiao, C., 2021. Location of Airbnb and hotels: the spatial distribution and relationships. Tourism Review 77, 1-16. https://doi.org/10.1108/TR-10-2020-0476

Lefever, D.W., 1926. Measuring Geographic Concentration by Means of the Standard Deviational Ellipse. Am J Sociol 32, 88-94.

Lei, W.S., Lam, C.C., 2015. Determinants of hotel occupancy rate in a Chinese gaming destination. Journal of Hospitality and Tourism Management 22, 1-9. https://doi.org/10.1016/j.jhtm.2014.12.003

Leung, R., Au, N., Liu, J., Law, R., 2018. Do customers share the same perspective? A study on online

OTAs ratings versus user ratings of Hong Kong hotels. J Vacat Mark 24, 103-117. https://doi.org/10.1177/1356766716679483
Li, L., Lu, L., Xu, Y., Sun, X., 2020. The spatiotemporal evolution and influencing factors of hotel industry in the metropolitan area: An empirical study based on China. Plos One 15, e231438. https://doi.org/10.1371/journal.pone.0231438
Li, M., Chen, J., 2019. High-speed rail network in China: the contribution of fast trains to regional tourism and economic development. Tourism Review 75, 414-432. https://doi.org/10.1108/TR-12-2018-0197
Li, M., Fang, L., Huang, X., Goh, C., 2015. A spatial‑temporal analysis of hotels in urban tourism destination. Int J Hosp Manag 45, 34-43. https://doi.org/10.1016/j.ijhm.2014.11.005
Liu, X., Jiang, C., Wang, F., Yao, S., 2021. The impact of high-speed railway on urban housing prices in China: A network accessibility perspective. Transportation Research Part A: Policy and Practice 152, 84-99. https://doi.org/10.1016/j.tra.2021.08.006
Loukaitou-Sideris, A., Cuff, D., Higgins, T., Linovski, O., 2012. Impact of High Speed Rail Stations on Local Development: A Delphi Survey. Built Environment 38, 51-70. https://doi.org/10.2148/benv.38.1.51
Lu, C., Pang, M., Zhang, Y., Li, H., Lu, C., Tang, X., Cheng, W., 2020. Mapping Urban Spatial Structure Based on POI (Point of Interest) Data: A Case Study of the Central City of Lanzhou, China. Isprs Int J Geo-Inf 9, 92. https://doi.org/10.3390/ijgi9020092
Lyu, G., Bertolini, L., Pfeffer, K., 2020. Is Labour Productivity Higher in Transit Oriented Development Areas? A Study of Beijing. Journal of Economic and Human Geography 111, 652-670. https://doi.org/10.1111/tesg.12414
Mannone, V., 1997. Gares TGV et nouvelles dynamiques urbaines en centre ville: Le cas des villes desservies par le TGV Sud-Est. les Cahiers Scientifiques du Transport 31, 71-97.
Marco-Lajara, B., Claver-Cortés, E., Úbeda-García, M., Zaragoza-Sáez, P.D.C., 2014. Hotel Performance and Agglomeration of Tourist Districts. Reg Stud 50, 1016-1035. https://doi.org/10.1080/00343404.2014.954535
Masson, S., Petiot, R., 2009. Can the high speed rail reinforce tourism attractiveness? The case of the high speed rail between Perpignan (France) and Barcelona (Spain). Technovation 29, 611-617.
McKenzie, G., Janowicz, K., Gao, S., Gong, L., 2015. How where is when? On the regional variability and resolution of geosocial temporal signatures for points of interest. Computers, Environment and Urban Systems 54, 336-346. https://doi.org/10.1016/j.compenvurbsys.2015.10.002
Moulaert, F., Salin, E., Werquin, T., 2001. Euralille: Large-Scale Urban Development and Social Polarization. European Urban and Regional Studies 8, 145-160.
Newman, P., Thornley, A., 1995. Euralille: 'Boosterism' At the Centre of Europe. Eur Urban Reg Stud 2, 237-246. https://doi.org/10.1177/096977649500200303
Nield, Egan, D.J., Kevin, 2014. Towards a Theory of Intraurban Hotel Location. Urban Stud 37, 611-621.
Niu, F., Xin, Z., Sun, D., 2021. Urban land use effects of high-speed railway network in China: A spatial spillover perspective. Land Use Policy 105, 105417. https://doi.org/10.1016/j.landusepol.2021.105417
Okabe, A., Yamada, I., 2001. The K‑Function Method on a Network and Its Computational Implementation. Geogr Anal 33, 271-290. https://doi.org/10.1111/j.1538-4632.2001.tb00448.x
Ortega, E., López, E., Monzón, A., 2012. Territorial cohesion impacts of high-speed rail at different

planning levels. J Transp Geogr 24, 130-141. https://doi.org/10.1016/j.jtrangeo.2011.10.008

Pagliara, F., Mauriello, F., Garofalo, A., 2017. Exploring the interdependences between High Speed Rail systems and tourism: Some evidence from Italy. Transportation Research Part A: Policy and Practice 106, 300-308. https://doi.org/10.1016/j.tra.2017.09.022

Pan, Z., 2002. Market concentration ratio analysis of the international tourist hotel industry in Taipei area. Tourism Management Research 2, 57-66.

Reusser, D.E., Loukopoulos, P., Stauffacher, M., Scholz, R.W., 2008. Classifying railway stations for sustainable transitions – balancing node and place functions. J Transp Geogr 16, 191-202. https://doi.org/10.1016/j.jtrangeo.2007.05.004

Ribalaygua, C., Perez-Del-Caño, S., 2019. Assessing spatial planning strategy in high-speed rail station areas in Spain (1992-2018): towards a sustainable model. Eur Plan Stud 27, 595-617. https://doi.org/10.1080/09654313.2018.1564189

Ritter, W., 1986. Hotel location in big cities, In Vetter, F. (Ed.), Big City Tourism, Reimer,Berlin, pp. 355-364.

Rogerson, J.M., 2013. Reconfiguring South Africa's hotel industry 1990-2010: Structure, segmentation, and spatial transformation. Appl Geogr 36, 59-68. https://doi.org/10.1016/j.apgeog.2012.06.004

Schütz, E., 1998. Stadtentwicklung durch Hochgeschwindigkeitsverkehr, Konzeptionelle und Methodische Absätze zum Umgang mit den Raumwirkungen des schienengebunden Personen-Hochgeschwindigkeitsverkehr (HGV) als Beitrag zur Lösung von Problemen der Stadtentwicklung, Informationen zur Raumentwicklungs. Heft 6, 369-383.

Shi, Y., Tao, T., Cao, X., Pei, X., 2021. The association between spatial attributes and neighborhood characteristics based on Meituan take-out data: Evidence from shanghai business circles. J Retail Consum Serv 58, 102302. https://doi.org/10.1016/j.jretconser.2020.102302

Shoval, N., Cohen-Hattab, K., 2001. Urban hotel development patterns in the face of political shifts. Ann Tourism Res 28, 908-925. https://doi.org/10.1016/S0160-7383(00)00083-9

Sorensen, A., 2000. Land readjustment and metropolitan growth: an examination of suburban land development and urban sprawl in the Tokyo metropolitan area. Prog Plann 53, 217-330.

Sun, B., Yu, H., Peng, Z., Gao, Y., 2017. High-Speed Rail and Manufacturing Agglomeration: Evidence from Beijing–Guangzhou High-Speed Rail in China. Transportation Research Record Journal of the Transportation Research Board 2606, 86-95.

Trip, J.J., 2008. Urban Quality in High-speed Train Station Area Redevelopment: The Cases of Amsterdam Zuidas and Rotterdam Centraal. Planning Practice & Research 23, 383-401. https://doi.org/10.1080/02697450802423633

Van Doren, C.S., Gustke, L.D., 1982. Spatial analysis of the U.S. lodging industry, 1963–1977. Annals of Tourism Resesrch 9, 543-563. https://doi.org/https://doi.org/10.1016/0160-7383(82)90072-X

Villalba Sanchis, I., Insa Franco, R., Martínez Fernández, P., Salvador Zuriaga, P., Font Torres, J.B., 2020. Risk of increasing temperature due to climate change on high-speed rail network in Spain. Transportation Research Part D: Transport and Environment 82, 102312. https://doi.org/10.1016/j.trd.2020.102312

Wall, G., Dudycha, D., Hutchinson, J., 1985. Point pattern analyses of accomodation in Toronto . Ann Tourism Res 12, 603-618.

Wang, F., Chen, C., Xiu, C., Zhang, P., 2014. Location analysis of retail stores in Changchun, China: A street centrality perspective. Cities 41, 54-63. https://doi.org/10.1016/j.cities.2014.05.005

Wang, L., Cao, Y., Liu, K., 2012. Spatial Distribution and Clusters of Industry Nearby High-speed Rail

Station: The case of Nanjing Station, Shanghai-Nanjing Motor Train. Scientia Geographica Sinica 32, 301-307. https://doi.org/10.13249/j.cnki.sgs.2012.03.008

Wang, S., Mo, H., Lv, H., 2021. Industrial structure of high-speed railway station areas under the influence of location:Empirical evidences from POI data. Acta Geographica Sinica 76, 2016-2031.

Wang, S., Wang, J., Liu, X., 2019. How do urban spatial structures evolution in the high-speed rail era? Case study of Yangtze River Delta, China. Habitat Int 93, 102051. https://doi.org/10.1016/j.habitatint.2019.102051

Wenner, F., Thierstein, A., 2021. High speed rail as urban generator? An analysis of land use change around European stations. Eur Plan Stud, 1-24. https://doi.org/10.1080/09654313.2021.1946485

Willigers, J., 2008. The impact of high-speed railway developments on office locations: A scenario study approach, Physica-Verlag, pp. 237-264.

Xie, Z., Yan, J., 2008. Kernel Density Estimation of Traffic Accidents in a Network Space. Comput Environ Urban 32, 396-406.

Yang, Y., Luo, H., Law, R., 2014. Theoretical, empirical, and operational models in hotel location research. Int J Hosp Manag 36, 209-220. https://doi.org/10.1016/j.ijhm.2013.09.004

Yang, Y., Wong, K.K.F., Wang, T., 2012. How do hotels choose their location? Evidence from hotels in Beijing. Int J Hosp Manag 31, 675-685. https://doi.org/10.1016/j.ijhm.2011.09.003

Yi, B., Shi, D., Shi, F., Zhang, L., 2021. Do the flipped impacts of hotels matter to the popularity of Airbnb? Int J Contemp Hosp M 33, 2239-2263. https://doi.org/10.1108/IJCHM-06-2020-0582

Yokeno, N., 1968. La localisation de l'industrie touristique : application de l'analyse de Thunen-Weber, Cahiers du Tourisme, C-9. CHET, Aix-en-Provence.

Zeng, Z., Zhao, L., Wang, X., 2021. Does improved transportation promote innovation? evidence from China's cities. Appl Econ 54, 2643-2657. https://doi.org/https://doi.org/10.1080/00036846.2021.1992344

Zhang, X., 2021. Does high-speed railway strengthen the ties among nearby regions? Evidence from China. Asian Transport Studies 7, 100039. https://doi.org/10.1016/j.eastsj.2021.100039

Zhu, H., Liu, J., Liu, H., Wang, X., Ma, Y., 2017. Recreational Business District boundary identifying and spatial structure influence in historic area development: A case study of Qianmen area, China. Habitat Int 63, 11-20. https://doi.org/10.1016/j.habitatint.2017.03.003