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Sensing the Nighttime Economy–Housing Imbalance from a Mobile Phone Data Perspective: A Case Study in Shanghai

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Abstract: Sensing the nighttime economy–housing imbalance is of great importance for urban planning and commerce. As an efficient tool of social sensing and human observation, mobile phone data provides an effective way to address this issue. In this paper, an indicator, mobile phone data-based nighttime economy–housing imbalance intensity, is proposed to measure the degree of the nighttime economy–housing imbalance. This indicator can distinguish vitality variations between sleep periods and nighttime activity periods, which are highly related to the nighttime economy–housing imbalance. The spatial pattern of the nighttime economy–housing imbalance was explored, and its association with the built environment was investigated through city-scale geographical regression analysis in Shanghai, China. The results showed that the sub-districts of Shanghai with high-positive-imbalance intensities displayed structures with superimposed rings and striped shapes, and the sub-districts with negative imbalance intensities were distributed around high positive-intensity areas. There were significant linear correlations between imbalance intensity and the built environment. The multiple influences of built environment factors and related mechanisms were explored from a geographical perspective. Our study utilized the social sensing data to provide a more comprehensive understanding of the nighttime economy–housing imbalance. These findings will be useful for fostering the nighttime economy and supporting urban renewal.

Keywords: nighttime economy; economy–housing imbalance; urban vitality; mobile phone data; built environment

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1. Introduction

The nighttime economy refers to the economic activities that take place in the evening, such as eating out, drinking, and shopping [1,2]. With rapid urbanization and continuous improvements in residential life, the expansion of the nighttime economy has enriched the lives of residents, stimulated consumption, and significantly shaped the structure of urban activity spaces [3–5]. In the context of the vigorous development of the nighttime economy, the imbalance development of the nighttime economy and housing in specific areas has led to many issues, such as insufficient material supply, public safety, transportation congestion, and urban environmental governance [6]. For example, neighborhoods with nighttime economic activities that far exceed the demand of local residents may generate considerable noise and light pollution, which bothers native residents [7]. In contrast, neighborhoods with insufficient nighttime economic activities may not meet the demand of residents, and nighttime travel may be dangerous [8,9]. Therefore, sensing the nighttime economy–housing imbalance is of great importance.

The nighttime economy has attracted attention in many research fields, such as economics, urban planning, geography, and the social sciences [3,10,11]. A growing body of research has focused on sensing the nighttime economy patterns and uncovering its associations with social, economic, and built environment factors [7,12–14]. These researchers applied multiple data source, including survey, nightlight images, and human observation data, to explore related issues such as how nighttime economic activities agglomerate in cities, why it appears in those specific places, and the corresponding planning strategies and public policies to promote the nighttime economy [10,15]. However, although these researches have successfully identified the nighttime economy pattern and its general determinations, the imbalance development of nighttime economy and housing has not been adequately explored.

With the increased popularity of smart devices, mobile phone data has become an effective tool for social sensing and human observation [16,17]. Mobile phone data have the advantages of wide spatiotemporal coverage, massive volumes, and fine temporal scale [18–20]. Such data can be utilized to distinguish the vitality variations in fine spatiotemporal granularity, therefore providing the opportunity to sense the imbalance development of nighttime economy and housing from an empirical perspective. Therefore, this study sets out to sense the imbalance development of the nighttime economy and housing by using mobile phone data. The central questions to be addressed in this study are: (1) How to quantitatively measure the imbalance development between nighttime economy and housing? and (2) How does the built environment affect the imbalance development of the nighttime economy and housing?

To answer these questions, we propose a novel indicator, mobile phone data-based nighttime economy–housing imbalance intensity (MP-NEHII), to quantitatively measure the trend and extent of the imbalanced development between nighttime economy and housing. This indicator is defined as the vitality variations between the time periods of nighttime social activity and residential activity, thereby providing a more comprehensive understanding of nighttime economy studies. The associations between the imbalance intensity and multiple built environment factors were explored from a geographical perspective to determine the driving mechanism of the nighttime economy–housing imbalance. On this basis, the nighttime economy–housing imbalance intensity pattern in the city of Shanghai was sensed using the proposed indicator, and several possible implications for promoting the balanced development of the nighttime economy and housing were discussed.

The remainder of this paper is organized as follows. We summarize the literature related to the research question in Section 2. The case study area and the data used are introduced in Section 3. The methodology is introduced in Section 4. The analysis results are presented in Section 5, and the discussion is presented in Section 6. Finally, the conclusions are presented in Section 7.

2. Literature Review

2.1. Exploration of Nighttime Economy Pattern

According to the datasets used, the relevant studies can be divided into two categories: field survey-based studies and multisource urban data-driven studies. Field survey-based studies sense nighttime economy information related to human activities and psychological responses through field surveys and preliminarily identify nighttime economy patterns in many cities [7,21]. For example, Li et al. conducted a field survey to obtain the nighttime recreational characteristics of tourists in Fuzhou, China [21]. Schwanen et al. extended the literature on nighttime activity inequality through a field survey analysis of visitors' presence in public spaces [22]. These studies preliminarily identified nighttime economy patterns. However, field surveys are expensive and provide limited samples; therefore, they cannot be used to cover all cities [23,24]. Moreover, in the context of complex field surveys, participants may become bored, thereby leading to recall problems [25].

To address these problems, researchers have shifted to methods that rely on statistical urban big data, including nighttime light satellite images, POI data, and built-up area data [26,27]. Cui et al. proposed a comprehensive nighttime economy index that integrated nighttime light satellite images, POI data, and socioeconomic statistical data [12]. They found that the nighttime economy intensity is highly associated with lifestyle, climatic, and cultural customs. Liu et al. identified high nighttime activity areas and their social functions using remote sensing data and POIs, which provided details on the spatial pattern of nighttime activities throughout the city [28]. These studies indicated that the pattern of the nighttime economy could be estimated through geographical proxies. However, the limitation of the long data update period of remote sensing data and POI data makes it fail to distinguish the differences between residential activities and other nighttime activities.

With the development of ICT and positioning techniques, the enormous amount of geotagged human activity data (e.g., taxi data, social media data, and mobile phone data) enables us to measure human activity at a finer spatiotemporal resolution [29–31]. Compared with the abovementioned datasets, geotagged human activity data offer advantages such as large volume, wide spatiotemporal coverage, and fine granularity [17,20]. Although these data have not been widely used to explore nighttime economy patterns, the study of vitality provides inspiration for the study of nighttime economies, and particularly for the nighttime economy–housing imbalance [32–34]. For example, Kim applied a functional principal component analysis to detect the nighttime period of cities and used pedestrian traffic data to portray nighttime vitality patterns in the city of Seoul, South Korea [32]. Wu and Niu used the number of active and stationary mobile phone users per unit area to measure the vitality and quantitatively analyze the influence of the built environment on vitality [13]. These studies can provide a theoretical basis and methodological support for sensing the imbalance development of the nighttime economy and housing.

2.2. Measurement of Imbalance Development in Urban Areas

Reducing inequality and developing sustainable cities and communities are two of the 17 goals in the United Nations Sustainable Development Goals, which were designed to be a blueprint for achieving a better and more sustainable future for all [35]. As an important precondition for achieving these goals, it is important to measure the imbalance of development in urban areas. The most instructive for our research is the measurement of job-housing imbalance, which reflects the imbalanced development of workplace and housing [36]. Researchers have developed a variety of indicators to measure the job-housing imbalance development from the perspectives of ratio, difference, and travel cost. For example, Giuliano and Small proposed the classical indicator that refers to the distribution of employment relative to the distribution of workers within a given spatial unit [37]. Xiao et al. used the spatial mismatch index, which describes the spatial relationship difference between employment and population in a certain region, to capture job–housing imbalance on a fine scale [21]. Sultana and Zhou et al. used the commuting time/distance as the intuitive indicators to measure the job–housing imbalance, which can be used in both aggregates and disaggregate analysis [38,39]. Excess commuting can also be seen as a travel cost-based measurement of jobs–housing imbalance, which is defined as the difference between the actual commuting time and the shortest possible commuting time [40]. Furthermore, it is worth noting that the commonly used indicators in measuring social inequality, activity accessibility, and activity diversity can be used in the measurement of imbalance development in urban areas [41]. These indicators provide a reference for sensing the nighttime economy–housing imbalance.

The application of geotagged human activity data provide opportunity to investigate the imbalance development in a costless way. For example, Frias-Martinez et al. proposed a framework to estimate the commuting pattern with mobile phone data and validated its effectiveness by capturing the same pattern with survey data [42]. Yang et al. analyzed the spatiotemporal pattern of commuting convergence and divergence by the differences between inflows and outflows using mobile phone data [43]. Gao et al. combined the smart card data and vehicle plate data to analyze social inequality with indicators such as activity diversity and accessibility [44]. These studies validate the effectiveness of using geotagged human activity data to measure the imbalance development in urban areas and provide technical support for our analysis of nighttime economy–housing imbalance.

3. Study Area and Datasets

3.1. Study Area

The city of Shanghai was selected to conduct this study. Shanghai is the largest city in China, and it is one of the most populous cities in the world, with a population of 24.28 million in 2019. Shanghai is the economic, financial, trade, and shipping center of China. The gross domestic product (GDP) of Shanghai was 381.55 billion in 2019, ranking first out of all Chinese cities [45]. According to the Shanghai master plan 2015–2040 [46], Shanghai designated the area of the city within the outer ring road as the core urban area. Considering the research data density and data interpretability, 118 sub-districts within the outer ring road of Shanghai (also the historical and commercial center of Shanghai) were selected as the study area. This area is a typical modern metropolitan area with high urban density, a complex built environment, and a high mobile phone penetration rate. Moreover, the sub-districts are the basic administrative unit which hold the local authority for urban governance and urban planning in China. As the focus of this study is to sense the nighttime economy–housing imbalance and to further support nighttime economy planning, the sub-district, which is treated as the basic unit in routine urban management, was selected as the spatial unit for subsequent analysis [33]. Maps of the study area are shown in Figure 1.

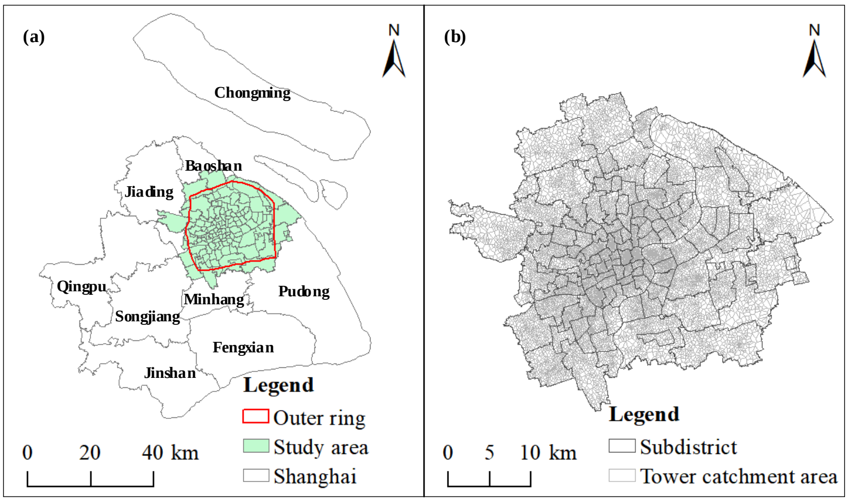

Figure 1. Maps of (**a**) Shanghai and (**b**) the study area.

3.2. Datasets

The mobile phone data were provided by a mobile communications firm in Shanghai for scientific research. It records information such as user ID, location, timestamp, and the type of event (phone call, message, periodic update, power on and off, tower handover, etc.) when a phone interacted with the mobile phone tower. The records were contributed by a random sample of over 1 million subscribers in the city of Shanghai from 3 September to 9 September 2012. According to its annual report [47], this mobile communications operator serves approximately 64% of all residents, which indicates this dataset has the advantage of massive user and wide spatiotemporal coverage. To mitigate the influence of signal oscillation, an outlier test and elimination algorithm were used for data preprocessing [48]. Moreover, the nearest-neighbor interpolation algorithm was used to reconstruct the raw trajectories into hourly trajectories [49]. An individual's mobile phone data is shown as an example in Table 1. Note that personally identifiable information was eliminated to protect privacy. In addition, the recorded locations are the positions of cell phone towers, with a positioning error of between 100 m and 1000 m (according to the statistical report of the data provider based on the specific area, e.g., urban and rural areas), and the average time interval between two consecutive records was approximately 20 min. These data were thus able to meet our requirements for studying the nighttime economy–housing imbalance.

Table 1. Example of mobile phone data.

User ID	Date	Time (t)	Longitude (x)	Latitude (y)	Event Type
5c493 **	1	08:15:11	121.46 **	31.24 **	Call (inbound)
5c493 **	1	09:17:12	121.45 **	31.24 **	Message (receive)
5c493 **	1	09:33:27	121.45 **	31.24 **	Periodic update
5c493 **	...	...	...	...	
5c493 **	7	21:13:06	121.47 **	31.25 **	Call (outbound)
5c493 **	7	22:01:19	121.47 **	31.25 **	Handover

** Detailed information was obscured due to the data usage rules.

Four types of data were used to sense the built environment in Shanghai: POI data, road network data, metro line station data, and bus station data. The POI data record the specific points with a social activity function [50]. The dataset covers the whole study area and contains approximately 1.05 million records. It includes information such as the name, address, location (latitude and longitude), and type of POI. To facilitate subsequent analysis, we summarized the POI data into seven categories: "Company", "Shopping", "Public Service", "Residence", "Food", "Entertainment", and "Education". The typical subcategories and the distributions of each POI category are shown in Table A1 and Figure A1 in Appendix A, respectively. The road network, metro line station, and bus station data were used to sense the convenience of transportation in the study area. Specifically, the road network records reflected the geometry of each road segment, and the metro line station and bus station data recorded the name, address, location, and the number of bus/metro lines for each station. Over 7500 km of roads, 1161 metro line stations and 5402 bus stations were included in the study. The overall distribution of these four types of data is shown in Figure 2.

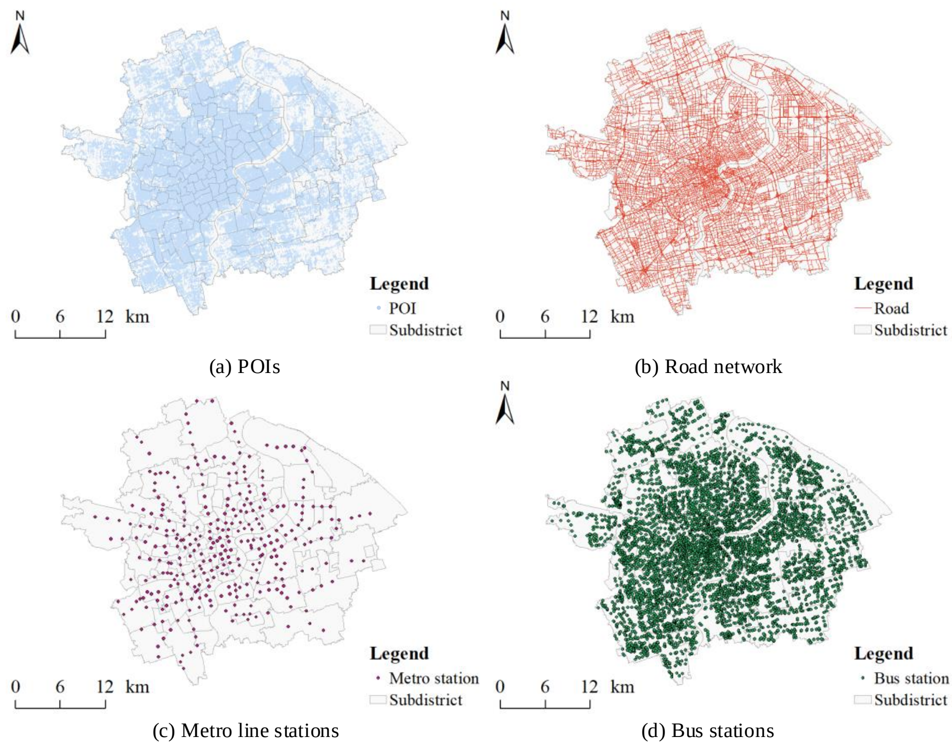

Figure 2. Overall distribution of (**a**) POIs, (**b**) Road network, (**c**) Metro line stations, and (**d**) Bus stations.

4. Methods

4.1. Nighttime Economy–Housing Imbalance Intensity

A novel indicator, mobile phone data-based nighttime economy–housing imbalance intensity (MP-NEHII), is introduced in this study. The basic connotation of the nighttime economy–housing imbalance in this study was as follows: within a given area, the difference in vitality between nighttime activity and sleeping periods. This definition reflected the gap between the supply volume of nighttime activity and residential activity in a certain area. An imbalance intensity greater than 0 in a sub-district indicated that the vitality during the period of nighttime activity was more than the vitality during the period of sleep. This suggested that the supply volume of nighttime economic activity in these sub-districts was greater than the supply volume of residential activity, which also indicated that these sub-districts have higher nighttime consumption and activity levels than resident levels (hereafter referred to as activity units). In contrast, an imbalance intensity lower than 0 in a given sub-district indicated that the unit was mainly residential (hereafter referred to as residential units). The calculation process contained two steps: the estimation of hourly vitality distribution and the division between the nighttime economy and sleeping periods.

Considering the general linear relationships between the number of mobile phone users and the population, the hourly mobile phone user density of each sub-district unit was selected as the indicator to represent vitality. The mobile phone data were interpolated into hourly trajectories during preprocessing; thus, the total number of mobile phone users for each tower at each time can be easily calculated. Because the boundaries of the mobile phone tower catchment areas and the sub-district units are not exactly the same (as shown in Figure 1b), we used the areas as the weights in calculating the number of mobile phone users within each sub-district unit. Therefore, the hourly mobile phone user density could be calculated as follows:

$$\varepsilon_{j,t} = \frac{\sum_1^M \frac{A_{m\cap j} * \partial_{m,t}}{A_m}}{A_j} \tag{1}$$

where $\varepsilon_{j,t}$ represents the density of hourly mobile phone users in sub-district unit j at time t, $\partial_{m,t}$ represents the number of hourly mobile phone users of cell phone tower m at time t, A_m represents the tower catchment area of tower m, A_j represents the area of sub-district unit j, $A_{m\cap j}$ represents the area of the intersection between sub-district unit j and the catchment area of tower m, and M represents the total number of towers with catchment areas that intersect sub-district unit j, where $\forall m \in [1, M)$.

The division of the nighttime economy and sleeping periods was another key step in calculating the nighttime economy–housing imbalance intensity. To determine the corresponding time periods, the window size was first calculated. Considering that the autocorrelation function is commonly used to measure the correlation between a time series and its delayed version, it is widely used for time window selection [51]. Therefore, the average vitality series over all sub-districts in the study area was calculated to represent the global vitality variation pattern, and the variation in temporal autocorrelation of the average vitality series over different window sizes was calculated with the following formula:

$$\rho_\delta = \frac{E[(\varepsilon_t - \bar{\varepsilon})(\varepsilon_{t-\delta} - \bar{\varepsilon})]}{\sigma^2} \tag{2}$$

where ρ_δ represents the autocorrelation value with time window size δ, ε_t represents the average vitality at time t, $\bar{\varepsilon}$ represents the mean value of the average vitality series, and σ represents the standard deviation of the average vitality series. In this study, the autocorrelation value was close to zero when the time window size was 3. Therefore, the length of both the nighttime activity period and the sleeping period was set to 3 h.

Based on the habits of residents in Shanghai, the correlation of vitality at different times was subsequently introduced to determine which 3 h should be used to represent the corresponding time periods. In this study, we assumed that the determined representative time span should reflect the overall characteristics of the vitality distribution during the nighttime activity period and sleeping period. Therefore, the sum of the correlations was an indicator of period deviation. We initialized the nighttime activity period and the sleeping period as 17:00–24:00 and 0:00–7:00, respectively, based on prior knowledge. Then, the correlation of the vitality between each pair of times in the corresponding time periods was calculated (the results are shown in Tables A2 and A3 in Appendix A). By calculating the sum of the correlation values of each of the three consecutive hours, the highest values were obtained from 19:00 to 22:00 in the initialized nighttime activity period and from 2:00 to 5:00 in the initialized sleeping period. The analysis results are consistent with our common sense. Therefore, in this study, we defined the period of nighttime activity as 19:00 p.m. to 22:00 p.m. and the period of sleeping as 02:00 a.m. to 05:00 a.m.

After obtaining the hourly vitality distribution and the corresponding time periods, the imbalance intensity was calculated based on the average vitality difference between the nighttime activity periods and the sleeping periods. The calculation process is shown in Formula (3):

$$I_j = \frac{\sum_{t\_na_s}^{t\_na_e} \varepsilon_{j,t}}{t\_na_e - t\_na_s} - \frac{\sum_{t\_sl_s}^{t\_sl_e} \varepsilon_{j,t}}{t\_sl_e - t\_sl_s} \tag{3}$$

where I_j represents the MP-NEHII in sub-district unit j; t_na_e and t_na_s represent the end time and start time of the period of nighttime activity, respectively; and t_sl_e and t_sl_s represent the end time and start time of the period of sleep, respectively. Notably, the imbalance intensity is defined as the difference in vitality between the nighttime activity and sleeping periods rather than their ratio. This is because a ratio-based metric could be the same in densely populated areas and sparsely populated areas, while the corresponding influences could be quite different. Future studies will consider more ways to measure the imbalance intensity.

4.2. Built Environment

The influence of the built environment on human activities has been investigated in the literature [52,53]. Based on our literature review, we classified the built environment factors into three dimensions: density, transport accessibility, and land-use diversity. For the density dimension, the density of each POI category was calculated. For the transport accessibility dimension, the weighted road density, the metro line station density, and the bus station density were obtained to represent transportation flexibility. The weights were represented by the number of road lanes, the number of metro lines passing through a station, and the number of bus routes passing through a station. Moreover, the Shannon entropy metric was used to measure land-use diversity [54]; the calculation process is shown in Formula (4), where $p(j)$ represents the percentage of a specific category of POI among all POIs.

$$Ent_i = -\sum_{j=1}^{n} p(j) \log_2 p(j) \tag{4}$$

4.3. Statistical Analysis

Spatial autocorrelation analysis was used to assess the spatial pattern of the nighttime economy–housing imbalance intensity. Spatial autocorrelation captures the correlation among values of a single variable strictly attributable to their relatively close locational positions on a two-dimensional surface, introducing a deviation from the independent observation assumption of classical statistics [55]. Moran's I index is an important indicator used to measure spatial correlation. In this study, both the global Moran's I [56] and local Moran's I [57] indicators are used. Specifically, the global Moran's I reflect whether the nighttime economy–housing imbalance intensity pattern is clustered, dispersed, or random, and the local Moran's index can be used to identify the spatial clusters with extreme imbalance intensity values and spatial outliers. The process was implemented using ArcGIS 10.6, and the results were further analyzed in Section 4.2.

A correlation analysis was subsequently conducted to explore the relationships between built environment factors and the MP-NEHII. Although the considered factors are continuous variables, the distribution of some factors is not conformed to the normal distribution, according to the Kolmogorov–Smirnov test with the standard normal distribution, as shown in Table A4. Therefore, Spearman's rho correlation metric was applied to measure the correlations between the imbalance intensity and built environmental factors [58].

Furthermore, the variations in socioeconomic phenomena are often affected by multiple factors [59,60]. Considering that the spatial relationship tends to vary in space, a geographically weighted regression (GWR) model was applied to explore the synergistic influence of built environmental factors on the nighttime economy–housing imbalance intensity [61]. This approach is an extension of the least square regression model, which relax the assumption that conditional relationships between the dependent variable and independent variables were constant over space. It provided a local approach that can reveal spatially varying associations. The regression equation can be represented as shown in Formula (5):

$$y_i = \beta_0(u_i) + \sum_{k=1}^{p} \beta_k(u_i)x_{i,k} + \mu_i \tag{5}$$

where $\beta_0(u_i)$ represents the coefficient corresponding to the location u_i, β_k represents the coefficient of the explanatory factor $x_{i,k}$ at location u_i, p represents the number of explanatory factors involved in the regression model, and μ_i represents the random error. The GWR model combines these separate equations by incorporating the dependent and explanatory effects within the bandwidth of each target feature. In this study, a Gaussian function was used to measure the geographical effects on the nighttime economy–housing imbalance, and the shape and size of the bandwidth were auto-selected on the basis of the Akaike information criteria [62].

5. Results

5.1. Statistical Analysis of the Nighttime Economy–Housing Imbalance

The nighttime economy–housing imbalance intensity in each sub-district unit was calculated. The statistical description of imbalance intensity is shown in Table 2. The imbalance intensity ranged from −215.42 to 676.49, with median and standard deviation values of 2.06 and 107.16, respectively. To capture a statistical description of the nighttime economy–housing imbalance, we divided the imbalance intensities into nine categories based on the natural break algorithm [63]. The frequency of each category is shown in Figure 3.

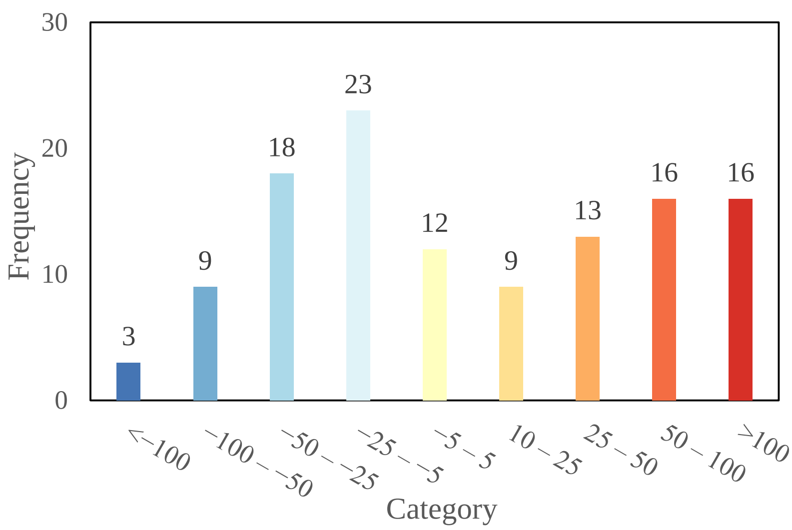

Figure 3. Frequency of each imbalance intensity category.

Table 2. Statistical description of nighttime economy–housing imbalance intensity.

N	Min	Max	Mean	1st Quartile	Medium	3rd Quartile	St. dev.
118	−215.42	676.49	31.66	−25.42	2.06	55.58	107.16

The results showed that the number of residential sub-districts with negative imbalance intensities was roughly equal to the number of sub-districts with positive imbalance intensities (53 vs. 54). However, the distribution of each category of residential units and activity units was different. Most residential units were distributed in categories for which the absolute value of the imbalance intensity was low. This means that in most residential units, the vitality during the sleep period was not that different from the vitality during the nighttime activity period. In contrast, most activity units were distributed in categories with high imbalance intensities. This phenomenon can be explained by the study area characteristics. For the residential units, the relatively convenient transportation and relatively mature supporting facilities in the study area have led to the formation of some residential units that foster nighttime activities. Thus, vitality differences between the sleep period and nighttime activity period are minimal. For the activity units, the relatively high land price has concentrated the use of activity units for activity types that can generate high value (such as office land and commercial land). The area of residential land is relatively low, and houses are expensive. Thus, some middle- and low-income residents who act in these units at night live in distant parts of the metropolitan area to balance living and transportation costs. This phenomenon was also reflected in the statistical results, where the absolute value of the maximum positive imbalance intensity was greater than the absolute value of the minimum negative imbalance intensity.

5.2. Spatial Patterns of the Nighttime Economy–Housing Imbalance Intensity

Figure 4 show the spatial distribution of the nighttime economy–housing imbalance intensity. Intuitively, the imbalance development of nighttime economy and housing is a relatively common phenomenon, and its spatial distribution shows spatial divergence. The activity units with high imbalance intensities exhibit a structure superimposing ring and stripe shapes. The ring-shaped area, which is also the core region of activity units, roughly coincides with the geometric center of Shanghai. This area includes many well-known landmarks, such as the Oriental Pearl TV Tower, the Lokatse, Nanjing Road, the Bund, and the People's Square; these are the traditional commercial and tourist centers of Shanghai. The stripe-shaped area runs through northern and southern Shanghai. By reviewing the public transportation map of Shanghai, we found that this strip basically follows the direction of Shanghai Metro Line 1. The metro line promoted the expansion of urban commercial spaces and business areas by providing fast, convenient, and orderly transportation. In turn, nighttime social activities have become popular in the units along the metro line. Most residential units are distributed near activity units, allowing residents to easily participate in nighttime activities; this overall distribution pattern reflects a relative balance between activity units and residential units in Shanghai.

To determine whether the spatial distribution of the imbalance intensity was spatially correlated and calculate the degree of correlation, the global Moran's I index was used. This index can reflect whether the obtained pattern is clustered, dispersed, or random, and it is often used to quantitatively describe dependence in space. According to the analysis results, the z-score equals 8.999, which is obviously greater than the strictest threshold value of 2.58. This result suggests that the imbalance intensity exhibits a significant clustered distribution pattern. Moreover, the p-value was close to 0, indicating that this result is reliable. This conclusion was consistent with Tobler's First Law of Geography: "Everything is related to everything else, but near things are more related to each other" [64]. Furthermore, the spatial clusters of units with high or low imbalance intensities and spatial outliers were detected using Anselin Moran's I index, as shown in Figure 5. The sub-districts were divided into five categories according to the results:

nonsignificant, high-high cluster, low-low cluster, high-low outlier, and low-high outlier. In this study, the high-high clusters represent densely concentrated nighttime activity sub-districts, the low-low clusters represent densely concentrated residential sub-districts, the high-low outlier clusters represent nighttime activity centers near densely concentrated residential sub-districts, and the low-high outlier clusters represent residential sub-districts near nighttime activity centers. The results suggested that the high-high clusters were associated with the geometric center of Shanghai, and there are some low-low clusters and high-low outlier areas near the high-high cluster area. This result further confirms the previously described spatial patterns.

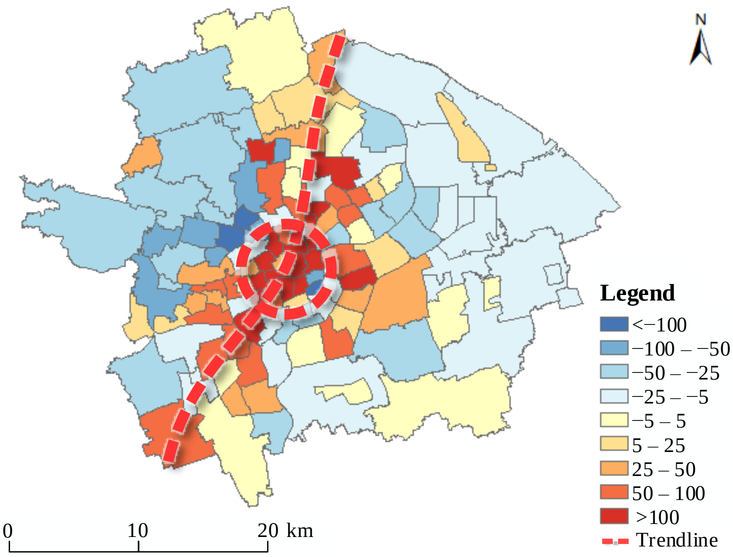

Figure 4. Distribution of the nighttime economy–housing imbalance intensity.

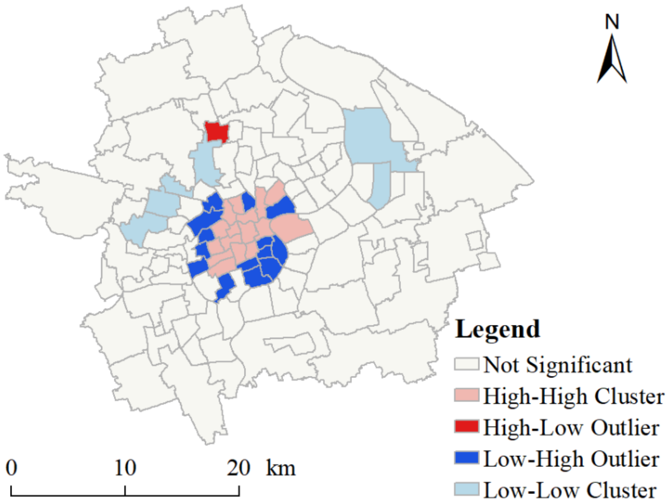

Figure 5. Local autocorrelation analysis results for the imbalance intensity distribution.

5.3. Associations between the Imbalance Intensity and Built Environment Factors

In this section, the associations between the imbalance intensity and built environment factors were analyzed to explore the mechanism through which the nighttime economy–housing imbalance is formed. First, a correlation analysis was conducted to assess the relationships between various factors and the imbalance intensity. The analysis results are shown in Table 3. The metric r represents Spearman's rho correlation coefficient, which reflects the linear correlation between each built environment factor and the imbalance intensity, and the *p*-value represents the probability that the correlation occurred by chance.

The results showed that there were significant linear correlations between the imbalance intensity and all built environment factors ($p < 0.01$). In terms of the density dimension, the company, education, food, and entertainment POI densities were strongly related to the imbalance intensity, with correlation coefficient values larger than 0.4. This finding was consistent with the results of previous studies: overtime work at companies and nighttime tutoring lessons at education institutions lead to people gathering in the corresponding spatial units, and dining and entertainment activities were the main forms of nighttime economic activities [14,65]. The residence, shopping, and public service POI densities exhibited relatively weak correlations. In terms of the transport accessibility dimension and land use diversity dimension, the factors were positively correlated with the imbalance intensity. This result indicates that the higher land-use diversity and better accessibility, the higher the nighttime economy–housing imbalance intensity. This phenomenon can be explained as the flexible travel services provide residents with easy access to gathering in these spatial units. The high land-use diversity indicates multiple and diverse facilities in this area, including types such as public service, food, and entertainment. It can satisfy the diverse need for the economic activities of residents and helps facilities potentially serve complementary functions [59,66]. Meanwhile, the relatively high cost of living makes few people live in these areas [67,68], thus making the nighttime economy–housing imbalance intensity higher. The results of the above correlation analysis provide some basis for the selection of parameters for the subsequent regression analysis.

Table 3. Relationships between built environment factors and nighttime economy–housing imbalance intensity.

Metric	Density							Travel Accessibility			Diversity
	Company	Shopping	Service	Residence	Food	Entertainment	Education	Road	Metro	Bus	Entropy
r	0.481 **	0.347 **	0.434 **	0.258 **	0.460 **	0.441 **	0.478 **	0.383 **	0.396 **	0.327 **	0.243 **
p-value	0.000	0.367	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008

** Correlation is significant at the 0.01 level.

To avoid the adverse effect of the multicollinearity problem, seven explanatory factors, company, residence, shopping, entertainment, public service, bus stations, and POI entropy, were selected through a collinearity test (condition number < 30), and all the factors were standardized with the z-score algorithm. The R^2 and adjusted R^2 values of the fitted GWR model were 0.8245 and 0.6973, respectively, which were significantly higher than the estimation result of the OLS regression model (0.490 for R^2 and 0.457 for adjusted R^2). This finding indicated that the proposed regression model is acceptable for exploring the mechanism driving the formation of the nighttime economy–housing imbalance from the perspective of the built environment. The coefficient distributions for the GWR results are shown in Figure 6, and the statistical descriptions of the coefficients are shown in Table 4.

Table 4. The statistical descriptions of regression coefficients.

Factors	Mean	Median	St. dev.	Minimum	Maximum
Company	94.81	75.92	80.37	−6.03	254.93
Residence	18.42	21.62	46.26	−76.70	116.72
Shopping	32.39	31.53	43.31	−65.21	114.58
Entertainment	24.16	27.73	55.63	−175.34	149.20
Public service	−87.62	−65.74	91.16	−271.72	140.16
Station	8.54	2.92	37.75	−54.56	79.87
Entropy	48.90	18.09	62.74	−19.80	241.23
Intercept	12.84	27.05	38.42	−99.36	70.83

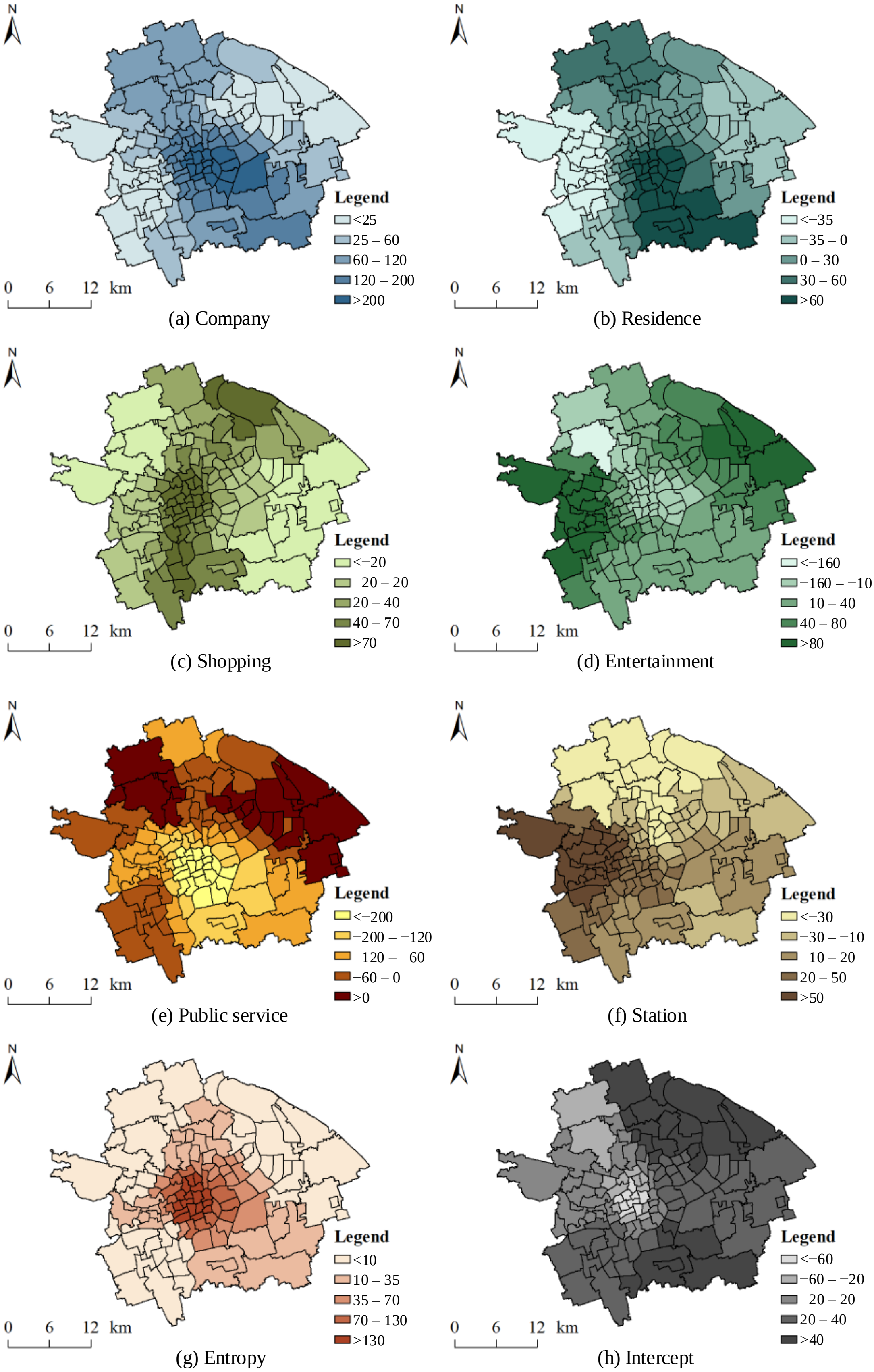

Figure 6. Coefficient distribution of the geographical weighted regression results: (**a**) Company; (**b**) Residence; (**c**) Shopping; (**d**) Entertainment; (**e**) Public service; (**f**) Bus station; (**g**) POI entropy; (**h**) Intercept.

The company, residence, shopping, entertainment, and public service POI densities were used to measure the effects of the nighttime economy–housing imbalance in the density dimension. The coefficient of company density reflected the positive impacts of companies on imbalance intensity. The high-value units were mainly distributed in the central area of Shanghai and nearby areas to the southeast and northwest (shown in Figure 6a). The northwest area was one of the main regions with industrial parks, and the central area and southeast area were the main regions with financial and commerce firms. This phenomenon reflects the agglomeration effect of company clustering on imbalance intensity; that is, a dense company distribution is associated with increased nighttime economic activities [69]. The distribution of the residence density coefficients displayed a gradually decreasing trend from the central area to the surrounding areas, and this trend was roughly related to the distribution of house prices in these areas (shown in Figure 6b). This phenomenon can be explained by the consumption levels of residents. The units with high consumption levels often included comprehensive supporting nighttime economic facilities and low residential density, as reflected by the positive influence on the nighttime economy–housing imbalance. The surrounding units had few supporting facilities and high residential density, leading to a negative impact on the nighttime economy–housing imbalance. The shopping POI coefficients reflected the positive impacts of consumption on the nighttime economy–housing imbalance in most units and the high-value-area distribution was roughly consistent with the direction of Shanghai Metro Line 1 (shown in Figure 6c). This trend reflects the positive influence of business and shopping activities on the nighttime economy–housing imbalance and implicates the role of public transport, especially metro lines, in promoting commercial development to a certain extent. The coefficients of the entertainment POI density reflected the generally positive effects of entertainment facilities on the nighttime economy–housing imbalance, with the high-value-unit distribution pattern being roughly opposite those for the company and residence POI densities (shown in Figure 6d). These findings reflect the potential for developing the entertainment industry to promote nighttime economic activities in various areas. In addition, the public service POI density displayed negative effects on the nighttime economy–housing imbalance. This phenomenon can be explained by the convenience of public service facilities as an important condition for housing site selection. Public service facility accessibility is more important for residential choices than for participating in nighttime economic activities [70,71].

The bus station density coefficient was used to measure the effects of transportation accessibility on the nighttime economy–housing imbalance intensity in the transport accessibility dimension. The various coefficients generally exhibited a positive impact on the nighttime economy–housing imbalance. The distribution presented an increasing trend from northwest to southeast (shown in Figure 6f); this distribution is related to the main residential areas in Shanghai, such as the Minhang District, Songjiang District, and Qingpu District, which is located in the southwestern part of the metropolitan area. An increase in transportation convenience in this area would promote the development of the nighttime economy.

POI entropy was used to measure the effects of land use diversity on the nighttime economy–housing imbalance intensity in the diversity dimension. The coefficients of POI entropy also reflected the positive association between the mixed and complementary land-use types and the nighttime economy–housing imbalance intensity. Notably, increasing the mixing of land use can help satisfy the nighttime activity demands of residents and attract individuals from underdeveloped areas to these areas. This finding was generally consistent with the research conclusions on vitality presented by Tu et al. and Yue et al. [53,59]. Moreover, the intercept factor also had a certain impact on the nighttime economy–housing imbalance intensity. The corresponding distributions are shown in Figure 6h.

It is worth noting that the selection of explanatory factors will significantly affect the analysis results. Three criteria were used in this study to support the selection of explanatory factors. First, we must ensure that there are no highly locally correlated explanatory variables in the geographically weighted regression model to avoid estimation errors induced by local multicollinearity problems [72]. Second, a combination of explanatory factors with higher adjusted coefficients of determination (adjusted R-square) is preferred to ensure that the model can represent the proportion of the variance in the dependent variable well [73]. Third, the combination with more explanatory factors that have a strong influence on prior knowledge is preferred to more comprehensively explain variation in the dependent variable. Based on the above criteria, even though the explanatory factors of food and education are highly correlated with the imbalance intensity, they were not applied in the regression model due to the highly local correlation with many other factors. In addition, taking into account the determination coefficient value, the importance of the public transportation system in urban travel, and the coverage in the study area, the explanatory factor of bus station density was chosen as the representative factor of traffic accessibility. The selection of explanatory variables may vary due to the difference in data characteristics in the study area.

6. Discussion

6.1. Insights into the Nighttime Economy–Housing Imbalance

With the acceleration of urbanization and the improvement of residents' living standards, the nightlife of residents has become increasingly important. However, the misaligned development of the nighttime economy has caused public safety issues, transportation congestion, environmental pollution, and urban management problems. In this study, we investigated the nighttime economy from the perspective of the nighttime economy–housing imbalance. This concept is derived from the job-housing imbalance addressed in the field of urban planning [36]. The basic definition of the nighttime economy–housing imbalance in this study is given as follows: within a given area, the vitality variations between the time periods of nighttime social activity and residential activity. If there is no major difference, it indicates that the supply volume of nighttime economy activity and residential activity in these areas is roughly equal. It implies that local residents can conduct nighttime leisure activities with short-distance travel. In contrast, an imbalanced phenomenon will increase the cost of nighttime activities and may lead to long-distance travel. Moreover, urban management problems may occur. For example, a high-positive-imbalance region (where the supply volume of nighttime economic activity is far greater than the demand of local residents) may result in considerable noise and light pollution, thus bothering local residents [7]; a negative-imbalance region may not be able to meet the nighttime leisure activity requirements of residents, and nighttime travel will increase the safety risk of residents [8,9]. In this context, the balanced development of the nighttime economy and housing should be considered in nighttime urban design. However, in the absence of government guidance, the distribution choices for housing and nighttime economic activities are mainly affected by economic factors. Therefore, to promote the balanced development of the economy and housing and enhance the economic vitality of residential units at night, it is necessary to explore and understand the related trends and assess the nighttime economy–housing imbalance.

6.2. Accessment of the MP-NEHII Indicator

A novel mobile phone data-based indicator, MP-NEHII, was proposed to measure the nighttime economy–housing imbalance intensity. By using the ubiquitous mobile phone as sensors, this indicator can distinguish the vitality variations between the time period of nighttime social activity and residential activity with the merits of massive users, wide spatiotemporal coverage, and fine granularity. Since the accuracy of this indicator depends on the accuracy of the measure of vitality, we validated this indicator by comparing the vitality of the time period of residential activity with the census data at the sub-district level. The R-square equals 0.733, indicating that this indicator can reflect the human activity well. Moreover, by measuring differences in vitality across time, the proposed indicator helps refine most nighttime economic studies that treat the nighttime economic activity as a whole time period to a dynamic change process. This can be used to measure the discontinuity in the use of commercial space, which can be especially important in times of quarantine. Furthermore, by constructing similar indicators, it is possible to explore issues such as differences in the distribution of nighttime economic activities during different time periods.

Considering that researchers may have difficulty accessing cell phone data, we propose several possible data sources as alternatives. For example, census data and population distribution data produced based on spatialization methods (such as GPWv4 and LandScan [74,75]) can be used to measure the vitality of the time period of residential activity. However, since these data tend to be updated over a long time period, the analysis errors caused by data being collected at different times should be alert. As for the vitality of the time period of nighttime economic activity, the nightlight image data, building data extracted from remote sensing images, maps of transportation and commercial centers, and the POI data can be used as substitutes. Worth noting that these data usually can only reflect the number of facilities supplied for nighttime economic activities and cannot reflect the vitality of residents' nighttime economic activities. That is, it's hard to know how many people carried out activities at these facilities during a specific time. Moreover, other types of human observation data, such as check-in data, take-out order data, and operating vehicle data, can be used to sense the nighttime economy–housing imbalance intensity in a similar way. However, there is a gap between these data and mobile phone data in terms of data representativeness [76]. These problems alternative data may affect the credibility of the analysis results to some extent.

There are still several limitations in this indicator that need to be further discussed. First, the analysis results of this indicator are influenced by the positioning accuracy of the mobile phone data, which depends on the density of the mobile phone tower. As the case area is the core urban area of one of the largest cities in China, the density of mobile phone towers is high (the average nearest distance between two mobile phone towers is about 90 m, as shown in Figure 1). It makes the data positioning accuracy can meet the analysis requirements when using subdistrict as the basic analysis unit. When data with higher positioning accuracy and spatiotemporal coverage are available, it will be possible to support the analysis of nighttime economy–housing imbalance at a finer granularity. Additionally, the low coverage of mobile phone data for children and the elderly can affect the analysis results. Second, the MP-NEHII is estimated through vitality variation while ignoring population movements among different regions and the human activity type. It is possible to further improve the interpretability of the results by calculating the nighttime flows of people in different areas and recognizing the individual activity type at night. Furthermore, the MP-NEHII is defined as the vitality difference between the sleep period and nighttime activity period rather than the corresponding ratio. Notably, the imbalance intensity may be the same as the ratio in densely populated areas and sparsely populated areas, but the determination is quite different. Further studies could consider additional ways to measure the imbalance intensity.

6.3. Implications for Mitigating Nighttime Economy–Housing Imbalance

The spatial distribution of the nighttime economy–housing imbalance intensity and the associations between the intensity and various built environment factors are discussed in Section 4. Based on the above context, several implications are discussed to enhance the economic vitality of residential units at night.

(1) Shopping. The general positive association between shopping POI density and the nighttime economy–housing imbalance intensity is shown in Figure 6c. This result indicates that the increasing shopping facilities in these areas are likely to promote the nighttime economy. It is worth noting that the high-coefficient units are located along Shanghai Metro Line 1. A possible reason for this phenomenon may be the combined effect of the long-passed metro line and shopping facilities on the nighttime economy, which was consistent with Wu and Niu [13]. In addition to Metro Line

1, there are several other metro lines that pass-through Shanghai's metropolitan area. Enriching the shopping facilities around other subway stations in areas with negative imbalance intensities and thus concentrating the population and diversifying commercial options could be a potential option. This may provide people living in these areas with convenient night leisure activities and promote nearby consumption by residents, thereby facilitating the overall nighttime economy–housing balance.

(2) Entertainment. Entertainment is another important nighttime social activity in addition to dining and shopping. Various nighttime entertainment activities, such as night landscape tours and scenic tours, have enriched nighttime economy development. Combined with Shanghai's goals of becoming an art center and an e-sport center, the development of characteristic entertainment industries in areas with negative imbalance intensities, such as e-sport competitions and musical dramas, could be considered to promote nighttime economy–housing imbalance. These activities allow tourists to experience Shanghai's culture and provide leisure space for residents, thereby cultivating nighttime economy vitality in these areas.

(3) Transportation. The coefficients of bus station density suggest that transportation accessibility has a generally positive association with vitality at night, especially in the western part of the Shanghai metropolitan area. It suggests facilities such as roads, bus stations, and subway stations may provide flexible travel and opportunities for the resident to carry out nighttime economic activities. Moreover, appropriately extending the operating time of public transportation, increasing the number and coverage of night buses, and encouraging the night operation of taxis in specific areas may be possible auxiliary ways to breed new nighttime economic centers and thus alleviate the overall nighttime economy–housing imbalance.

(4) Mixed land use. The regression analysis results indicate that increasing land-use diversity may be an efficient approach for promoting the nighttime economic activities in the residential units. Areas with balanced development among various land-use types may meet the nighttime leisure requirements of most nearby residents, thereby reducing travel costs and safety risks. However, facility locations for various land use types are affected by various interests, which can lead to uneven development. Therefore, reasonable urban planning and policy guidance is necessary.

7. Conclusions

This paper focused on an important but not yet properly addressed issue: the imbalance development of the nighttime economy and housing. A novel indicator, MP-NEHII, was proposed to measure the nighttime economy–housing imbalance intensity based on mobile phone data. It can distinguish the variations in vitality between human nighttime social activity and sleep periods, thereby improving the temporal scale of nighttime economic research. With the proposed indicator, the spatial pattern of the nighttime economy–housing imbalance was sensed, and the associations between the imbalance intensity and built environment factors were assessed through a city-scale analysis in the city of Shanghai, China. The results indicated that the imbalance development of nighttime economy and housing is a relatively common phenomenon, and its spatial distribution shows obviously spatial divergence. The areas with positive imbalance intensities are mainly distributed around urban centers and rail transit, and areas with negative imbalance intensities were distributed mainly around positive intensity areas. The profiling results indicated that built environment factors, including the company, residence, shopping, and entertainment POI density, bus station density, and POI diversity, displayed generally positive impacts on the imbalance intensity, and the public service factor exhibited a negative impact on the imbalance intensity. These findings could be used to identify the areas that might have a high nighttime economic capacity and the factors that should receive increased attention to promote nighttime economy–housing balance development.

This study indicated that mobile phone data could be used to measure urban nighttime economic patterns from a relatively fine-scale perspective. The findings in this study improve our understanding of the complex interrelations between urban economic and human activities and, to some extent, can improve the effectiveness of nighttime economy planning. Furthermore, these results can help government organizations measure discontinuity in the use of commercial space and thus build a livable and sustainable city by promoting a safe, accessible, and sustainable nighttime leisure system.

A number of future research directions could be considered. First, considering the limitations of the single time phase and the inability to conduct intervention and variable control, an empirical analysis was used in this study to explore the associations between the nighttime economy–housing imbalance and the built environment. However, it's worth noting that purely correlative analysis is not equipped for reasoning under such interventions and hence is prone to biases. Causal analysis models for geographical phenomena may be a meaningful attempt to further enhance the credibility of the analysis results in implications. Second, multiple types of POI density were used as indicators to measure the built environment. POI data mostly abstract the specific place function as a point, thus ignoring information such as its size and volume. Data that better reflect the urban built environment could be used, and the links between the imbalance intensity and various social, economic, and urban-development indicators could be discussed in future studies. Subsequently, this study only considered relationships at the sub-district level. To develop a full picture of nighttime human activity density, additional studies at other levels are needed. Last but not least, mobile phone data has the advantage of being able to accurately characterize the volume of human activity, and remote sensing data has the advantage of broad spatial coverage. The combination of these two types of data may help achieve a large-scale measure of nighttime economy–housing imbalance, thus supporting reducing inequality and the development of sustainable cities and communities. We will focus on these issues in future work.

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Data Availability Statement: Data are available on request due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The typical sub-categories of each POI category.

Category	Typical Sub-Categories
Company	Enterprise Organization Government Industry Park
Shopping	Shopping mall Grocery Pedestrian street Shopping center Department store

Table A1. *Cont.*

Category	Typical Sub-Categories
Public Service	Hospital Bank Beauty salon Gas station
Residence	Villa Apartment Hotel House
Food	Restaurant Buffet Bakery Grill Drive-in restaurant
Entertainment	Museum Cinema Scenery spots Pub Carnie Nightclub Gym Fitness
Education	School College Kindergarten Training institution

Table A2. Correlation coefficients of vitality between each two times in the nighttime activity period.

	17:00	18:00	19:00	20:00	21:00	22:00	23:00
17:00	1	0.992 **	0.972 **	0.954 **	0.932 **	0.907 **	0.894 **
18:00	0.992 **	1	0.992 **	0.981 **	0.965 **	0.945 **	0.934 **
19:00	0.972 **	0.992 **	1	0.996 **	0.987 **	0.974 **	0.966 **
20:00	0.954 **	0.981 **	0.996 **	1	0.996 **	0.987 **	0.981 **
21:00	0.932 **	0.965 **	0.987 **	0.996 **	1	0.996 **	0.992 **
22:00	0.907 **	0.945 **	0.974 **	0.987 **	0.996 **	1	0.999 **
23:00	0.894 **	0.934 **	0.966 **	0.981 **	0.992 **	0.999 **	1

** Correlation is significant at the 0.01 level.

Table A3. Correlation coefficients of vitality between each two times in the sleeping period.

	0:00	1:00	2:00	3:00	4:00	5:00	6:00
0:00	1	0.995 **	0.984 **	0.975 **	0.97 **	0.968 **	0.967 **
1:00	0.995 **	1	0.996 **	0.99 **	0.987 **	0.986 **	0.984 **
2:00	0.984 **	0.996 **	1	0.998 **	0.996 **	0.996 **	0.994 **
3:00	0.975 **	0.99 **	0.998 **	1	0.999 **	0.999 **	0.998 **
4:00	0.97 **	0.987 **	0.996 **	0.999 **	1	0.999 **	0.999 **
5:00	0.968 **	0.986 **	0.996 **	0.999 **	0.999 **	1	0.999 **
6:00	0.967 **	0.984 **	0.994 **	0.998 **	0.999 **	0.999 **	1

** Correlation is significant at the 0.01 level.

Table A4. K-S test results for built environment factors.

Metric	Density							Accessibility			Diversity
	Company	**Shopping**	**Service**	**Residence**	**Food**	**Entertainment**	**Education**	**Road**	**Metro**	**Bus**	**Entropy**
Statistics	0.173	0.23	0.124	0.09	0.152	0.181	0.128	0.091	0.173	0.068	0.173
p-value	0.000	0.000	0.000	0.020	0.000	0.000	0.000	0.018	0.000	0.200	0.000

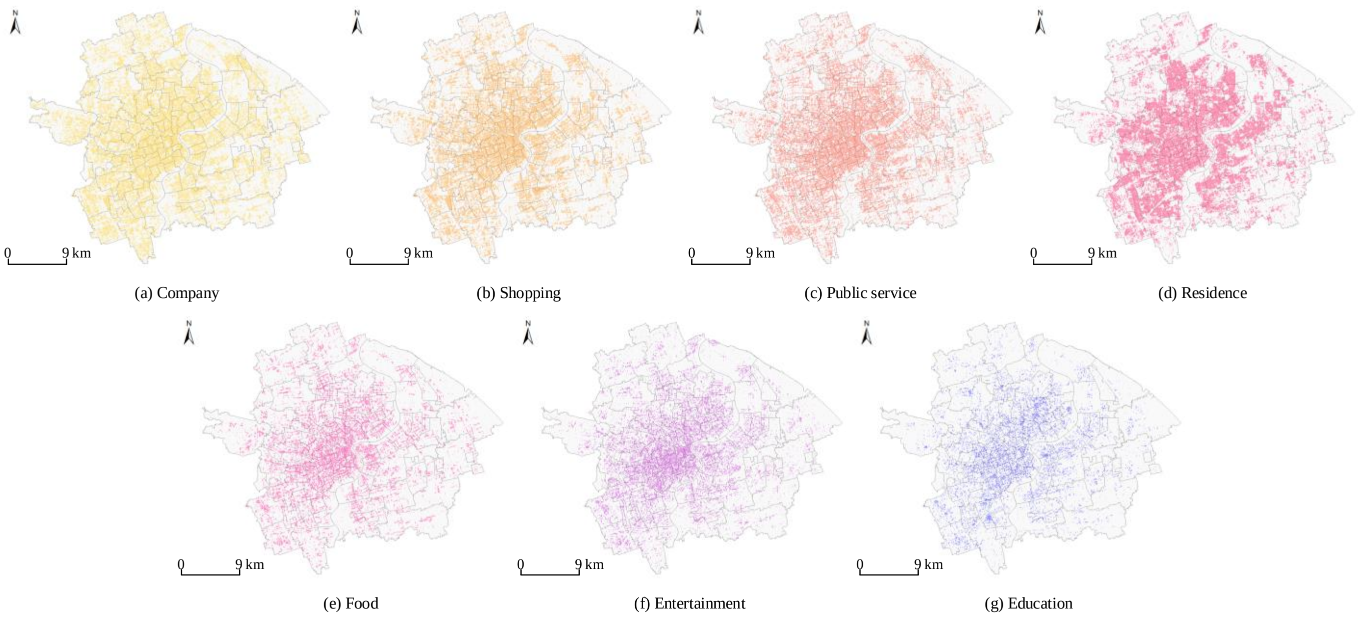

Figure A1. The distribution of POIs by category (each point represents a POI).

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