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Article

What Factors Revitalize the Street Vitality of Old Cities? A Case Study in Nanjing, China

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Abstract: Urban street vitality has been a perennial focus within the domain of urban planning. This study examined spatial patterns of street vitality in the old city of Nanjing during working days and weekends using real-time user datasets (RTUDs). A spatial autoregressive model (SAM) and a multiscale geographically weighted regression (MGWR) model were employed to quantitatively assess the impact of various factors on street vitality and their spatial heterogeneity. This study revealed the following: (1) the distribution of street vitality in the old city of Nanjing exhibited a structure centered around Xinjiekou, with greater regularity and predictability in street vitality on working days than on weekends; (2) eight variables, such as traffic location, road density, and functional density, are positively associated with street vitality, whereas the green view index is negatively associated with street vitality, and commercial location benefits street vitality at weekends but detracts from street vitality on working days; and (3) the influence of variables such as traffic location and functional density on street vitality is contingent on their spatial position. Based on these results, this study provides new strategies to enhance the street vitality of old cities.

Keywords: street vitality; residents' perceptions; multisource data; multiscale geographically weighted regression; the old city of Nanjing

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1. Introduction

Vitality is defined as the degree to which a settlement form supports life functions, ecological requirements, and human capabilities [1]. Urban vitality refers to the frequency and diversity of various economic, cultural, and social activities in a city, arising from the various social activities undertaken by residents in public spaces and serving as an important indicator to measure the level of urban development and competitiveness [2–5]. Within cities, areas with high vitality offer numerous advantages. Economically, these areas tend to be business hubs, hosting multiple employment opportunities and a range of comprehensive service facilities [6]. Culturally, these areas often offer a variety of activities that bolster the efficiency of residential interactions, thereby fostering innovation and entrepreneurship [7]. Socially, these areas are characterized by frequent interpersonal communication and strong social cohesion [8]. In recent years, rapid urbanization has propelled the level of urban development. However, it also poses a risk to urban vitality [9,10], particularly manifested in the gradual decline of vibrant traditional urban streets [2]. Street vitality, as a part of the urban space, is an important aspect of urban vitality [11]. Street vitality encompasses the extent of diversity and frequency of street activities, including shopping, commuting, socializing, and cultural engagements [2,5,12]. Streets with high vitality are typically highly attractive to residents, and can bolster happiness and community cohesion [8,13–15]. Street space is now widely recognized in the field of urban planning, and street vitality has emerged as a key issue in urban development. Urban planning theories, including New Urbanism and smart growth, emphasize the importance of street vitality [16,17]. Since 2000, various countries have implemented urban street design guidelines to steer and standardize the construction of local streets in alignment with local conditions, with the goal of creating more attractive streets [18].

Urban construction in China has shifted from incremental expansion to enhancing existing infrastructure, and urban renewal has emerged as a pivotal approach to urban development [19]. During urban renewal, the vitality of urban public spaces, particularly street vitality, plays a vital role in accommodating residents' needs at various levels, and is essential for optimizing urban development [20]. Pedestrians are the main group of people who use streets for various activities. The number of pedestrians on the street and the frequency of their activities directly reflect street vitality; more pedestrians indicate more social interactions, commercial activities, and cultural exchanges, i.e., higher street vitality [2,3,21]. Recently, cities such as Shanghai, Wuhan, and Xi'an in China have introduced street design guidelines that prioritize pedestrian needs and strive to balance traffic efficiency with pedestrian experience. Consequently, it is important to precisely assess the vitality of urban streets, investigate the determinants of street vitality, and devise strategies to invigorate them, thereby enhancing the quality of urban public spaces and achieving superior urban development.

Research on urban street vitality measurement has evolved from subjective to objective approaches, from qualitative to quantitative methods, and from traditional survey data to leveraging big data. Initially, studies typically obtained data through field observations [22], interviews [23,24], and questionnaire surveys [25] to measure street vitality. While these techniques can directly capture citizens' subjective perceptions and assessments, they are inefficient and unsuitable for sustained large-scale research. The onset of the big data era has prompted researchers to use multiple datasets, including real-time user datasets (RTUDs) [26], mobile phone data [27], and social media check-in data [28], to assess street vitality. Big data is characterized by its real-time nature, wide scope, and high accuracy, and allows for integrated spatiotemporal analysis, enabling more extensive and prolonged research.

Building on this foundation, scholars have conducted research on the determinants of street vitality, with a primary focus on locational conditions and built environment. Considering locational conditions, streets in prime locations—namely, those proximate to service amenities, including metro stations or commercial entities—are deemed to possess greater vitality [29–32]. Regarding the built environment, small-scale and compact streets are viewed as more dynamic because of their moderate construction density and appealing design [3,33–35]; simultaneously, urban streets that offer a variety of functions and mixed uses are perceived as more vibrant [2,16,23,36]. Moreover, streets that facilitate efficient commuting and those with a more transparent ground–floor interface are considered livelier [22,34]. Ultimately, to invigorate street vitality, urban planners have enacted measures for city development, including the integration of diverse functional zones, the expansion of pedestrian areas, and the enhancement of transportation access. In fact, along with the dimensions of location conditions and built environment, residents' subjective perceptions also significantly influence street vitality. Relevant studies demonstrated that residents' subjective experiences with urban streets, including comfort, security, enjoyment, and satisfaction, influence their selection of streets for diverse activities [37–42]. However, the impact of residents' perceptual factors on street vitality has not received sufficient attention. Therefore, unlike previous studies, the dimension of residents' perceptions was taken into account based on location conditions and built environment. Four variables related to residents' perceptions were selected for this study as potential influences on street vitality, making the indicators of influence richer and more comprehensive.

Contemporary research on street vitality has employed two scales. The first is the block scale, which typically examines a specific street or cluster of streets, concentrating on street interface elements and residents' particular activities, albeit with a limited scope and sample size [13,43]. The second is the urban scale, which encompasses the city's entire street network and often utilizes large-scale grids, such as a 500 m grid, to delineate streets and assess vitality [44,45]. However, these grid units exceed the street scale, posing challenges for the precise capture of street vitality and its critical determinants. To strike a balance between accurately capturing street-scale changes in vitality and the operability of data processing and analysis, a small-scale grid of 100 m was selected as the study unit. This study first uses a 100 m grid for the analysis of street vitality, primarily because it strikes a balance between capturing subtle spatial changes and keeping data processing and analysis tractable. The 100 m grid coincides with the street scale and provides a more accurate picture of street vitality while avoiding excessive computational complexity.

In summary, this research utilized the old city of Nanjing as a case study, using a 100 m fine-grained grid as the analysis unit. Initially, the RTUDs were employed to assess temporal and spatial patterns of street vitality in the old city of Nanjing. Subsequently, a range of determinants was analyzed using travel cost data, road network data, point of interest (POI) data, street view image (SVI) data, and social media commentary data. By integrating a spatial autoregression model (SAM) and a multiscale geographically weighted regression (MGWR) model, this study investigated the factors influencing and spatial variances of street vitality, to yield precise insights. This study addressed three key questions: (1) what are the characteristics of the spatial distribution of street vitality in the old city of Nanjing; (2) what are the factors impacting the vitality and the spatial variance in terms of their quantitative influence; and (3) what strategies can be employed in urban planning to enhance urban vitality?

2. Materials and Methods

2.1. Study Area

Nanjing is one of the central cities of the Yangtze River Delta and the capital of Jiangsu Province. It is also classified as one of China's national, historical, and cultural cities. Possessing a history of 2496 years, Nanjing balances modernity with its rich historical and cultural heritage. This study focused on the old city of Nanjing, which encompasses an area of approximately 41.5 square kilometers (Figure 1). The old city is encircled by the city walls of the Ming capital and preserves numerous historical elements within the area, including four historic urban areas: the southern part of the old city, the Ming Palace Museum, Gulou-Qingliang Mountain, and Beijing East Road. Furthermore, at the forefront of Nanjing's urbanization, the old city harbors a modern urban center, Xinjiekou. Streets in the old city of Nanjing exhibit varied functional characteristics, and the diversity of street types is indicative of the research scope. This study employed a 100 m grid as the analysis unit, capable of encompassing various street types and minimally impacted by the internal dynamics of urban blocks, offering greater precision than prior research. Based on this, grids without roads were removed, ultimately yielding 2265 grids (Figure 1).

2.2. Data Sources and Processing

2.2.1. Real-Time User Datasets (RTUDs)

Real-time user datasets (RTUDs), representing real-time information about the number of users in a given area, were collected with the consent of users who use location-based services such as Baidu, Tencent, and Meituan. Each data point of the RTUD represents an area of a specific range and contains the attributes of longitude, latitude, time, and count. The count attribute can represent the density of real-time users in this area, which can be used to portray street vitality. Prior research has indicated that RTUDs may serve as a reliable measure of vitality [26,44,46].

Given Tencent's substantial user base in China, this study utilized Tencent EasyGo data as the RTUD, and with an accuracy of 25 m, they were deemed appropriate for analyzing urban street scales. Following the COVID-19 outbreak, there was a significant reduction in the intensity of urban human activity [47]. Consequently, to circumvent the atypical manifestations of street vitality, this study used data collected from March to May 2018, gathering information at 2 h intervals from 10:00 to 20:00 on both working days and weekends. This study included 509,769 data entries.

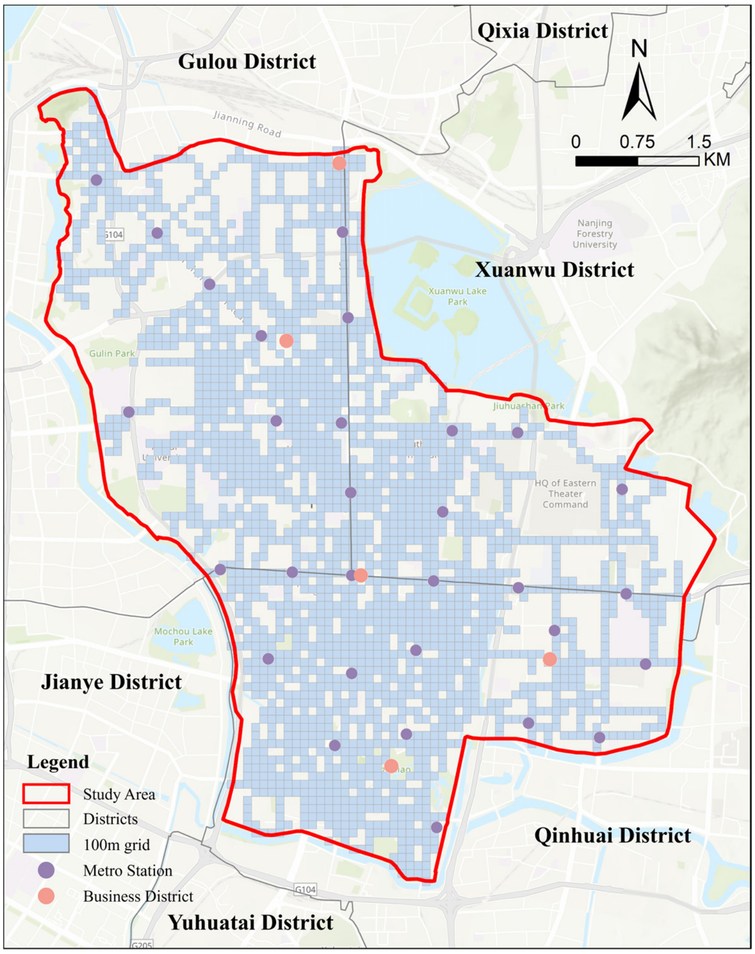

Figure 1. The 100 m grid of the study area.

2.2.2. Travel Cost Data

Travel cost is the actual time or distance required to travel from a facility's point of demand to its point of supply. Utilizing Amap's path planning API (https://lbs.amap.com/api/webservice/guide/api/newroute, accessed on 22 July 2024), this study identified each grid centroid point as the starting point and targeted subway stations and business centers in the study area as endpoints. A Python program was employed to calculate the shortest walking path from the starting point to the endpoint in batches, which served as the travel cost and foundation for assessing location conditions.

2.2.3. Road Network Data

Vector road network data were obtained from OpenStreetMap (OSM) (https://www.openstreetmap.org/, accessed on 22 July 2024). Initially, this study simplified the road network data. Given that expressways and tunnels lack the attributes of public spaces, their inclusion could introduce bias into our research findings. Consequently, expressways and tunnels within the research area were excluded, and the remaining roads were classified into four categories—main roads, secondary roads, branch roads, and alleyways—followed by the merging of lanes and simplification of the road network. With all roads depicted as single lines, the total length of the processed roads totaled 294.66 km (Figure 2).

Considering the visual range of human eyes and the intricacy of urban streetscapes, prior studies typically adopt a 50 m interval as suitable for collecting SVIs [48,49]. Consequently, this study established street view image collection points at every 50 m on each road, resulting in a total of 5886 points (Figure 2). Subsequently, the longitude and latitude coordinates of each point were computed and extracted from the batches. These served as foundational data for the acquisition of street view images.

Figure 2. Road network distribution and SVI sampling points.

2.2.4. Point of Interest (POI) Data

The point of interest (POI) data utilized in this study, sourced from the Amap open platform (https://lbs.amap.com/, accessed on 22 July 2024), were employed to calculate functional density and diversity. Amap is one of the most popular and largest online map service providers in China, and the POI data obtained from the Amap open platform perform well in terms of accuracy. Data were categorized into eight types: catering services, public facilities, shopping services, finance and insurance, science and education, cultural facilities, life services, sports and leisure, and accommodation services. A total of 35,335 data entries were analyzed within this framework.

2.2.5. Street View Image (SVI) Data

Street view image (SVI) data have been utilized globally, due to their extensive coverage and economical collection costs. In previous research, three data sources, Google Street View, Baidu Street View, and Tencent Street View, have been frequently used. Baidu SVI data were selected for this study based on the availability of images within the research scope and superior image resolution [50]. In addition, the panoramic mode of the SVIs, as opposed to the conventional one-point-four perspective, aligns more closely with the human visual field and subjective perception [51].

In this study, a web crawler script written in Python was utilized to invoke the Baidu API service interface (https://lbsyun.baidu.com/, accessed on 22 July 2024), facilitating batch retrieval of street view images using longitude and latitude coordinates. Initially, this study simulated the human visual field to adjust the horizontal and vertical angles of the line of sight and viewpoint position data. Subsequently, the photo collection period was restricted to the months of April–November to ensure that the vegetation in the images was lush, preventing any impact on overall spatial quality due to winter streetscapes. Due to the absence of street view data at certain locations, 5683 SVIs were ultimately amassed.

2.2.6. Social Media Commentary Data

Social media commentary data are the comments left by residents on social platforms after using service facilities, which represent users' subjective evaluations of the quality of a certain service facility. The social media commentary data used in this study were obtained from the Dianping website (https://www.dianping.com/, accessed on 22 July 2024), which is similar to Yelp. It is China's leading local information and transaction platform, and one of the world's earliest established independent third-party consumer review websites, capable of providing information such as merchant introduction, consumer reviews, and consumer offers. The social media commentary data we obtained contain the names and addresses of various consumption places and the number of favorite comments they have. Among them, the number of favorite comments was used to reflect residents' satisfaction with the service and thus their subjective experience. A total of 124,184 social media data entries were included. Through the "Spatial Join" tool in ArcGIS 10.7, we summed the number of favorite comments of consumption places in each grid and divided by the grid area to obtain the values of the service satisfaction index.

2.3. Methods

The research framework is illustrated in Figure 3. This study initially measured the spatial and temporal distribution characteristics of street vitality on working days and weekends using Tencent EasyGo data. Subsequently, through a literature review and field research, 11 potential factors were selected from three aspects: locational conditions, built environment, and residents' perceptions. Finally, the SAM and MGWR models were employed to explore the quantitative association and spatial variance of these factors affecting street vitality.

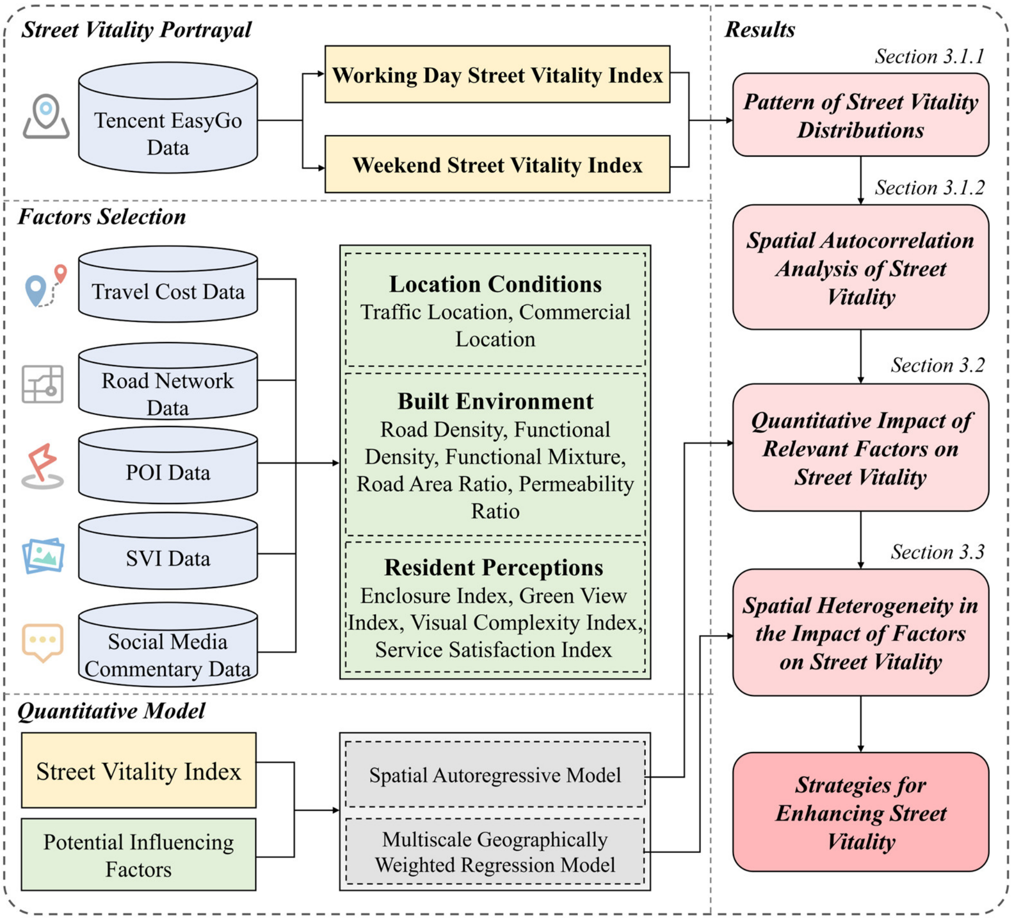

Figure 3. Research framework.

2.3.1. SVI Segmentation

The Pyramid Scene Parsing Network (PSP Net) model [52] was used to segment SVIs and determine the road area ratio, permeability ratio, green view index, enclosure index, and visual complexity index within the images. PSP Net is a deep-learning-based semantic segmentation network that captures contextual information via a pyramid pooling module that integrates both local and global information to yield more precise segmentation outcomes.

The open-source ADE20K dataset [53] was used to calibrate the model for semantic segmentation of Baidu SVIs. The ADE20K dataset is rich in content and includes 150 types of objects, including urban environmental elements. To calibrate the ADE20K dataset suitable for this study, we examined the streetscape images to ensure their clarity. Moreover, we excluded the unrelated objects in the ADE20K dataset and retained only those that were related to street vitality, which consisted of 21 types of objects, such as buildings, skies, trees, and fences [54].

In the segmentation process, we initially preprocessed the SVIs to ensure they were the same size and resolution, and suitable for the PSP Net model. Furthermore, these SVIs were input into the PSP Net model, which fused the feature maps with the original feature maps after pooling them at several scales through the PSP module. These were then classified through a convolutional layer to generate the category probability map for each pixel. Finally, the model generated semantic segmentation results by selecting the final category of each pixel with the maximum probability (Figure 4).

Figure 4. Workflow of semantic segmentation [52,53].

2.3.2. Variable Calculations

(1) Street Vitality Measurements

Street vitality is generated by residents engaging in various activities, including shopping, leisure, and commuting [55]. The aggregation of people within street spaces forms the foundation for these activities, and real-time gatherings and activities of the population within the street space can be used to measure street vitality. Street spaces should include the street itself and a range of surrounding functional areas [2,5]. In this study, the street range was defined using a 100 m grid and involved two sets of real-time user data collected on working days and weekends. Through the "Spatial Join" tool in ArcGIS 10.7, the RTUDs within each grid were connected to corresponding street vitality values on working days and weekends. The degree of population aggregation within each grid and each time period is of equal importance; thus, this study used the regular averaging method to summarize the resulting data. We summed the values represented by all the points in a grid and divided by the number of points to obtain the vigor value for that grid.

(2) Determination of Factors Influencing Street Vitality

Numerous factors have been shown to influence street vitality [29,33,37]. Firstly, a review of the literature indicates that existing studies primarily focus on physical environment elements, which we categorize into two dimensions: location conditions and built environment. Locational conditions encompassed traffic location (TL) and commercial location (CL), specifically the travel distance from the grid center to the nearest metro stations and business districts, calculated using Amap's path planning API. The built environment encompassed the road density (RD), functional density (FD), functional mixture (FM), road area ratio (RAR), and permeability ratio (PR), where RD is the total length of roads in a grid; FD is the density of functional facilities within a grid, calculated using the number of POIs; FM is the diversity of the POIs within a grid, calculated by Shannon entropy; and both RAR and PR were derived through SVI segmentation. Furthermore, there is some literature that mentions the enclosure index (EI) and green view index (GVI) as factors affecting street vitality [37–40]. In this research, we include the two factors of the residents' perception dimensions, as they represent the extent of street enclosure [13], and the prevalence of greenery [41] within the field of view, which can reflect residents' sense of security and comfort. Among these, EI is obtained by calculating "1 pixel minus the number of sky pixels". A higher number of sky pixels indicates more open street space and a lower EI [56]. Therefore, by calculating "1 pixel minus the number of sky pixels", a reverse indicator can be obtained, which can directly reflect the degree of enclosure. This method simplifies the calculation process and is widely used in such studies [57]. Through the literature review and field research, we also learned that enjoyment and satisfaction affect residents' choice of street when performing various activities [41,42]. Therefore, we added the visual complexity index (VCI) and service satisfaction index (SSI). The former, derived through SVI recognition, indicates the diversity of visual elements within the field of view [58], while the latter mainly reflects the subjective evaluation of residents, which is indicated through the number of favorable comments in the social media commentary data from the Dianping website. Ultimately, this study determined a total of 11 variables from 3 dimensions (Table 1).

Table 1. Descriptions of influencing variables.

Category	Variables (Abbrev.)	Formula	Description
Locational Conditions	Traffic location (TL) [29]	$TL_i = \lg(t_{i1} \times t_{i2})$	t_{i1} and t_{i2} are the distances from the i-th grid center to the nearest two different metro stations, respectively.
	Commercial location (CL) [32]	$CL_i = \lg(c_{i1} \times c_{i2})$	c_{i1} and c_{i2} are the distances from the i-th grid center to the nearest two different business districts (including the first-level business district Xinjikou, the third-level business districts Hunan Road and Fuzimiao, and the fourth-level business districts Ruijin Road and Zhongyangmen, a total of five places), respectively.
Built Environment	Road density (RD) [33]	$RD_i = \frac{RL_i}{A_i}$	RL_i is the total length of roads in the i-th grid, and A_i is the area of the i-th grid.
	Functional density (FD) [23]	$FD_i = \frac{POI_i}{A_i}$	POI_i is the number of POIs in the i-th grid.
	Functional mixture (FM) [36]	$FM_i = \exp(-\sum_{q=1}^{p} P_{iq} \ln P_{iq})$	p is the number of POI species, and P_{iq} is the proportion of the q-th POI in the i-th grid.
	Road area ratio (RAR) [22]	$RAR_i = \frac{1}{N}\sum_{j=1}^{N} \frac{R_{ij} + S_{ij}}{T_{ij}}$	N is the number of SVIs in the i-th grid, T_{ij} is the total pixels in the j-th image, and R_{ij} and S_{ij} are the numbers of pixels occupied by the car lane and sidewalk in the i-th image, respectively.
	Permeability ratio (PR) [34]	$PR_i = \frac{1}{N}\sum_{j=1}^{N} \frac{W_{ij} + D_{ij}}{W_{ij} + D_{ij} + B_{ij}}$	W_{ij}, D_{ij}, and B_{ij} are the numbers of pixels occupied by windows, doors, and buildings in the j-th image, respectively.
Residents' Perceptions	Enclosure index (EI) [13]	$EI_i = 1 - \frac{1}{N}\sum_{j=1}^{N} \frac{SKY_{ij}}{T_{ij}}$	SKY_{ij} is the number of pixels occupied by sky in the j-th image.
	Green view index (GVI) [41]	$GVI_i = \frac{1}{N}\sum_{j=1}^{N} \frac{G_{ij}}{T_{ij}}$	G_{ij} is the number of pixels occupied by greenery in the j-th image.
	Visual complexity index (VCI) [56]	$VCI_i = \frac{1}{N}\sum_{j=1}^{N} \exp(-\sum_{k=1}^{J} \ln P_{jk})$	J and P_{jk} represent the number of objects and the proportion of the k-th object in the j-th image, respectively.
	Service satisfaction index (SSI) [42]	$SSI_i = \frac{\sum_{m=1}^{M} FC_{im}}{A_i}$	M is the number of consumption places in the i-th grid, and FC_{im} is the number of favorite comments that the m-th place has from the social media commentary data in the i-th grid.

2.3.3. Spatial Autocorrelation Analysis

Moran's I index [59] is commonly used to determine whether the distribution of variables exhibits spatial autocorrelation. A Moran's I exceeding zero signifies a positive spatial correlation among the variables; conversely, a value less than zero indicates a negative spatial correlation. Moran's I can be categorized as global or local. Global Moran's I assesses the overall spatial autocorrelation of vitality within the study area, whereas local Moran's I examines the interrelations between each grid and its adjacent grids, thereby providing a more intuitive depiction of the local vitality agglomeration characteristics. The formulas for calculating global and local Moran's I are

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \quad (1)$$

$$I_i = \frac{N}{\sum_{j=1}^{N} W_{ij}} \frac{\sum_{j=1}^{N} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \quad (2)$$

where N represents the total number of grids, W_{ij} represents the spatial weight of the i- and j-th grids (i.e., the adjacency relationship between these two grids), x_i represents the vitality value of the i-th grid, and $\overline{x}$ represents the average vitality of all grids.

2.3.4. Global and Local Regression Models

Traditional linear regression models, such as the ordinary least squares (OLS) model, are often used to determine the correlation and significance of key factors [60]. The formula for the model is

$$y = \beta_0 + \sum_{j=1}^{M} \beta_j x_j + \varepsilon \tag{3}$$

where β_0 is the intercept, M is the total number of independent variables, x_j and β_j denote the value and coefficient of the j-th variable, respectively, and ε represents the random error term.

The OLS model assumes that observed values are mutually independent. However, the presence of spatial autocorrelation among variables violates this presupposition, leading to an underestimation of the influence of parameters from the independent to dependent variables, thereby affecting the model's fit [61]. This intricate issue was solved by the SAM [44], which incorporates the Lagrange multiplier (LM) robust diagnostic test. This test comprises two metrics: the LM (lag) and the LM (error). The robustness of these two metrics is assessed to determine the appropriate application of either the spatial lag model (SLM) or the spatial error model (SEM) within the SAM.

Obviously, street vitality varies spatially, and this variance is likely to exhibit certain characteristics within the study area; its relationship with the potentially influential factors is spatially non-stationary. Therefore, some studies have introduced local regression models [42,62,63]. Geographically weighted regression (GWR) models are frequently applied to address spatial non-stationarity. However, traditional GWR presupposes uniform spatial scales for all independent variables, potentially oversimplifying the spatial complexity. Introduced by Fotheringham in 2017, the MGWR model [64] relaxes the scale assumptions, permitting variable bandwidths for each independent variable, thereby enabling a regression analysis tailored to the optimal bandwidth of each factor. The formula for the MGWR model is as follows.

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{j=1}^{M} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \tag{4}$$

where β_{bw0} is the intercept under optimal bandwidth, (u_i, v_i) represent the coordinates of the barycenter of the i-th grid, bw_j represents the bandwidth of the j-th variable, x_{ij} and $\beta_{bwj}(u_i, v_i)$ denote the value and coefficient of the j-th variable, respectively, and ε_i represents the random error term of the i-th grid.

3. Results

3.1. Distribution Characteristics of Street Vitality

3.1.1. Pattern of Vitality Distributions

The natural breaks (Jenks) method [42] was used to discretize street spatial vitality in the old city of Nanjing, categorizing it into 1 to 5 levels from low to high (lowest = 1, highest = 5) (Figure 5). Overall, the spatial vitality distribution of streets in the old city of Nanjing was heterogeneous, yet a consistent single-center pattern was exhibited on both working days and weekends. Compared with the outlying regions, heightened street vitality was observed in the Xjiekou area (A in Figure 5), with more pronounced cluster agglomeration traits. Additionally, pockets of elevated vitality were interspersed within the peripheral zones. The street vitality of working days was robust in the southern sector and diminished in the northern sector, whereas the "core–periphery" dynamics were accentuated during weekends. These outcomes were likely correlated with proximity to metro stations and business districts.

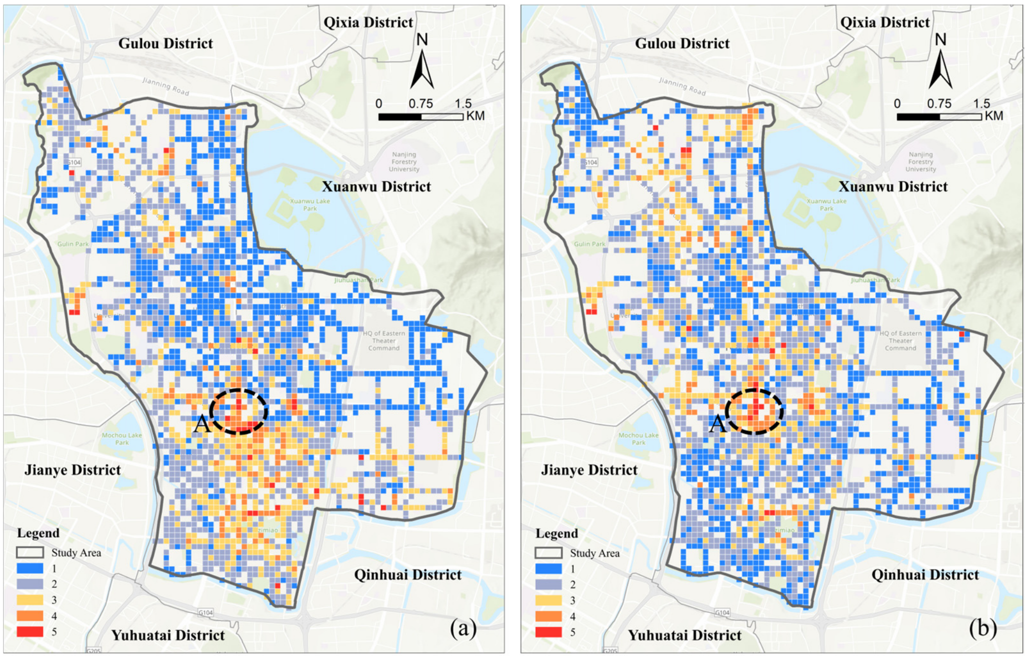

Figure 5. Spatial distribution of street vitality on working days (**a**) and weekends (**b**).

3.1.2. Spatial Autocorrelation Analysis of Street Vitality

Global Moran's I, indicating the street vitality within the old city of Nanjing, and associated statistics are presented in Table 2. At a significance level of 0.001, the maximum Moran's I values were 0.496 and 0.449 for working days and weekends, respectively, indicating a substantial positive spatial autocorrelation in street vitality. Vitality distribution was non-random and was correlated with various factors, including built environment and residents' perceptions, as indicated by pronounced clustering for these categories.

Table 2. Global Moran's I for street vitality on working days and weekends.

	Moran's I	z-Score	*p*-Value
Working Days	0.496	36.308	0.001
Weekends	0.449	34.209	0.001

Note: Moran's I is used to measure the spatial autocorrelation of variables, the z-score is used to react to the degree of aggregation or disaggregation of the dataset, and the *p*-value is used to indicate the confidence level. Number of permutations = 999.

Analysis of local spatial autocorrelation revealed that street vitality distribution within the study area exhibited marked spatial autocorrelation, resulting in four distinct clusters (Figure 6). These agglomeration groups were primarily characterized by "high–high" and "low–low" clusters, with a limited number of "high–low" and "low–high" outliers, indicating significant clustering in the distribution of street vitality. This pattern may stem from the spatial dynamics of resident movement, where residents traverse between identical or neighboring streets, and certain street focal points catalyze the congregation and dispersal of individuals.

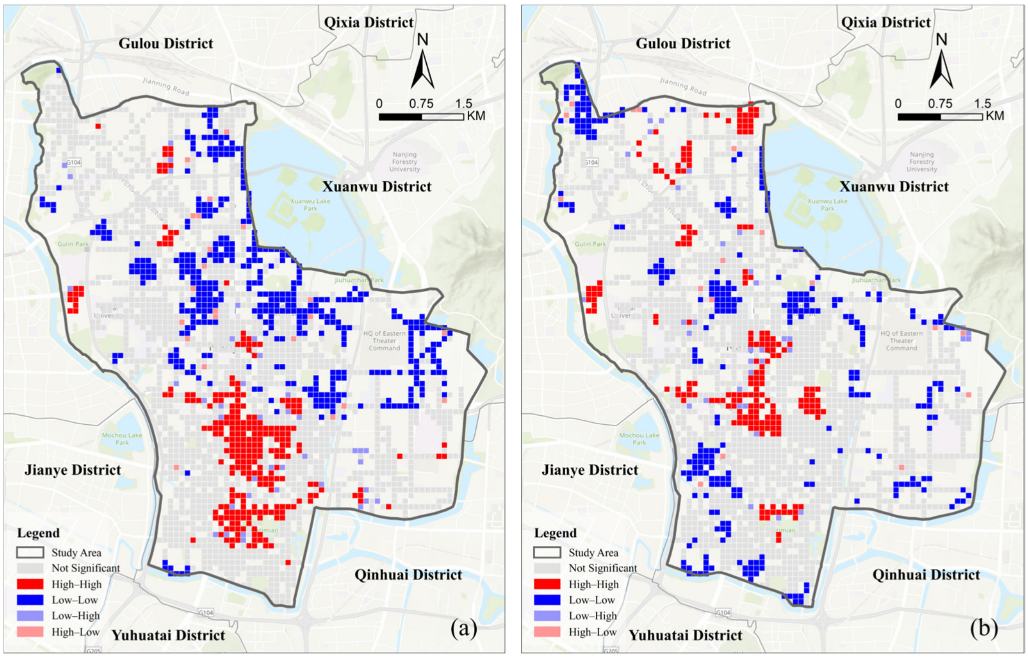

Figure 6. Clustering characteristics of street vitality on working days (**a**) and weekends (**b**).

3.2. Global Regression Analysis

After OLS regression analysis (Table 3), the LM robust diagnostic test was applied to the residuals. Given that the LM (error) exceeded the LM (lag) in magnitude and robustness (Table 4), SEM was ultimately chosen [31,63].

Table 3. OLS regression results on working days and weekends.

Category	Variable	VIF	Working Days		Weekends	
			Coef. (B)	Std.	Coef. (B)	Std.
	Intercept	--	0.001	0.018	0.001	0.018
Locational Conditions	TL	1.198	−0.097 ***	0.019	−0.002	0.019
	CL	1.241	0.130 ***	0.020	−0.084 ***	0.020
Built Environment	RD	1.098	0.048 *	0.019	0.039 *	0.018
	FD	1.511	0.390 ***	0.022	0.469 ***	0.022
	FM	1.475	0.095 ***	0.022	−0.018	0.021
	RAR	1.294	0.151 ***	0.020	0.065 **	0.020
	PR	1.009	−0.004	0.018	0.019	0.018
Residents' Perceptions	EI	2.704	0.093 **	0.029	−0.006	0.029
	GVI	2.922	−0.129 ***	0.030	−0.030	0.030
	VCI	1.290	0.067 ***	0.020	0.056 **	0.020
	SSI	1.118	0.019	0.019	0.075 ***	0.019
Overall Model-Fitting			AICc = 5673.76 Adjusted R^2 = 0.288		AICc = 5639.75 Adjusted R^2 = 0.298	

Note: *, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

Table 4. LM test results on working days and weekends.

	Working Days			Weekends		
	MI/DF	**Value**	***p***	**MI/DF**	**Value**	***p***
Moran's I (error)	0.2979	35.2021	0.0001	0.2275	26.9326	0.0001
Lagrange Multiplier (LM) (lag)	1	952.9891	0.0001	1	518.7896	0.0001
Robust LM (lag)	1	14.1159	0.0002	1	0.7998	0.0371
LM (error)	1	1195.9631	0.0001	1	697.3186	0.0001
Robust LM (error)	1	257.0899	0.0001	1	179.3288	0.0001
LM (SARMA)	2	1210.0790	0.0001	2	698.1184	0.0001

The variance inflation factors (VIF) for all variables were less than 5.0 (Table 3), indicating no multicollinearity among factors [65]. Synthesis of the data in Tables 3 and 5 resulted in adjusted R^2 values for the OLS model and SEM on working days of 0.288 and 0.415, respectively, whereas those on weekends were 0.298 and 0.376, respectively, suggesting that the explanatory power of the SEM surpasses that of the OLS model.

Table 5. SEM results on working days and weekends.

Category	**Variable**	**Working Days**		**Weekends**	
		Coef. (B)	**Std.**	**Coef. (B)**	**Std.**
	Intercept	0.002	0.035	0.005	0.031
Locational Conditions	TL	−0.168 ***	0.026	−0.057 *	0.025
	CL	0.118 ***	0.034	−0.056 *	0.031
Built Environment	RD	0.056 **	0.017	0.043 *	0.018
	FD	0.369 ***	0.022	0.461 ***	0.023
	FM	0.068 **	0.021	−0.012	0.021
	RAR	0.121 ***	0.019	0.060 **	0.019
	PR	−0.004	0.015	0.011	0.016
Residents' Perceptions	EI	0.063 *	0.028	0.031	0.029
	GVI	−0.099 ***	0.029	−0.055 *	0.030
	VCI	0.075 ***	0.019	0.058 **	0.019
	SSI	0.037 *	0.017	0.088 ***	0.018
Overall Model-Fitting		AICc = 5334.76 Adjusted R^2 = 0.415		AICc = 5452.31 Adjusted R^2 = 0.376	

Note: *, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

SEM regression indicated that street vitality was more predictable on working days than weekends, due to a more consistent pattern of resident activity on working days. This finding is consistent with the findings from other urban studies, such as in Chengdu [62]. Of the three categories, the built environment was most strongly correlated with street vitality, followed by locational conditions, and residents' perceptions. In addition to PR, other variables were associated with street vitality, with TL, RD, FD, RAR, VCI, and SSI positively correlated with street vitality, and GVI negatively correlated with street vitality. The correlation of TL and RAR with street vitality was significantly higher on working days than on weekends, suggesting that commuting is a pivotal factor influencing street vitality. The correlations for FD and SSI were stronger on weekends than on working days, reflecting residents' elevated expectations of service facility quantity and quality during weekends. Notably, FM and EI were only associated with street vitality on working days, and both were positively associated, whereas CL was positively associated with street vitality on weekends, with converse effects observed on working days.

3.3. Local Regression Analysis

The GWR and MGWR models were employed to assess influencing factors at the spatial scale (Table 6). Relative to the OLS and GWR models, the MGWR model exhibited a higher adjusted R^2 and lower corrected Akaike Information Criterion (AICc), demonstrating the enhanced explanatory power of the MGWR model regarding the influence of related factors on street vitality.

Table 6. Diagnostic information for regression models on working days and weekends.

	Working Days			**Weekends**		
	OLS	**GWR**	**MGWR**	**OLS**	**GWR**	**MGWR**
AICc	5673.76	5046.97	4872.96	5639.75	5155.83	4923.84
R^2	0.291	0.580	0.616	0.302	0.577	0.596
Adjusted R^2	0.288	0.526	0.560	0.298	0.514	0.552

Spatial distributions of the correlation of statistically significant ($p \leq 0.05$) influencing factors, from the MGWR analysis, are depicted in Figure 7 (working days) and Figure 8 (weekends). A deeper blue shade signifies a stronger negative correlation and a more intense red hue indicates a stronger positive correlation.

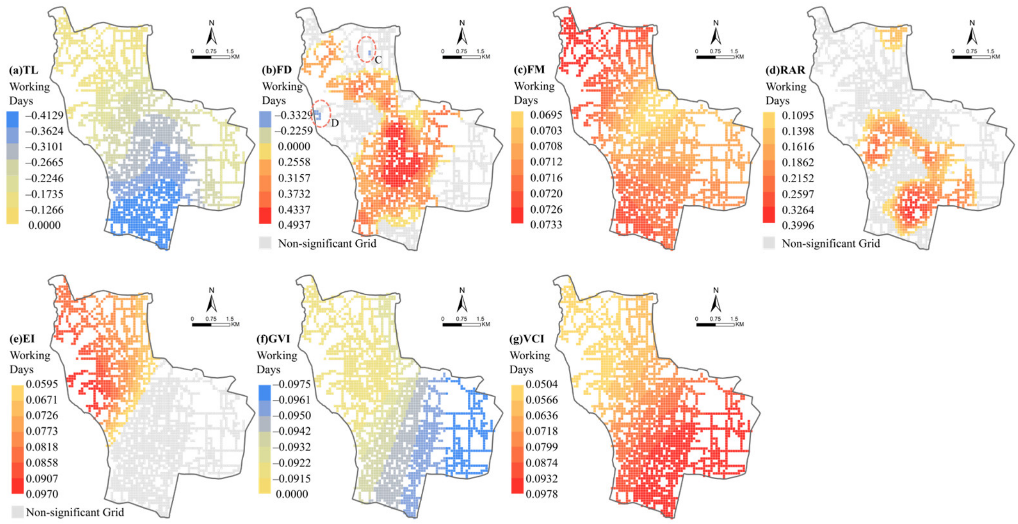

Figure 7. Coefficient distribution of selected influencing factors on working days.

TL was associated with significantly enhanced street vitality on working days, with its influence waning progressively from the south to the north of the city. This trend aligned with the spatial distribution of street vitality on working days (Figure 5a), indicating the role of commuting patterns in shaping street vitality. Of note, on weekends, only areas near business districts and some metro stations exhibited a positive impact, while areas around Zhongyangmen (A in Figure 8) and Sanpailou (B in Figure 8) showed a prominent negative impact on street vitality.

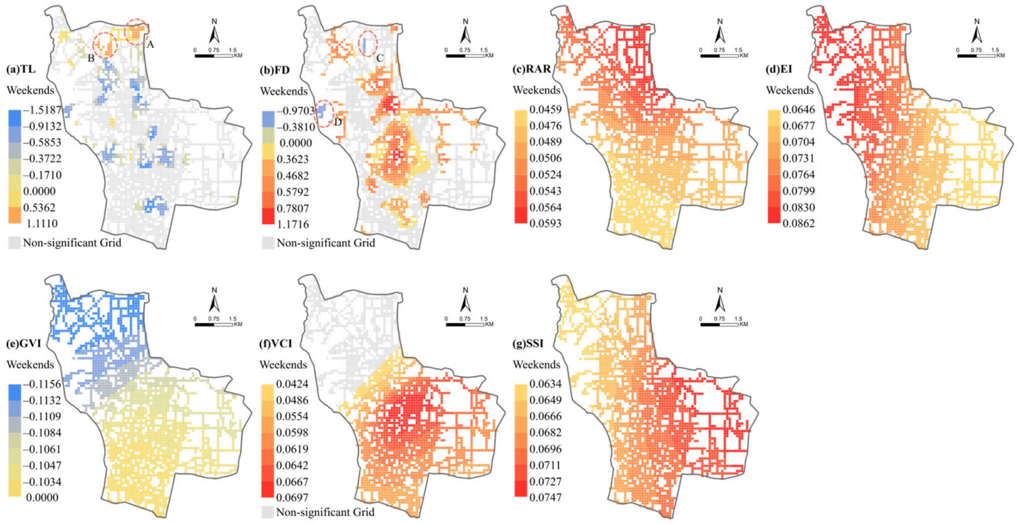

Figure 8. Coefficient distribution of selected influencing factors on weekends.

In addition to the proximity to several large entities (such as the National Electric Power Research Institute, C in Figures 7 and 8) and parks (such as Nanjing Stone City Ruins Park, D in Figures 7 and 8), FD was, generally, positively associated with street vitality. Areas of high impact were more concentrated on working days, whereas on weekends the dispersion extended to various business districts of different levels. The beneficial impact of the RAR on street vitality aligns with the spatial distribution of street vitality on working days (Figure 5a), underscoring the heightened activity along roads.

VCI was positively correlated with street vitality, particularly in the southern sector on working days and in the Xinjiekou area on weekends. This pattern aligns with the spatial distribution of street vitality (Figure 5), signifying that visual diversity is a key factor in resident engagement. Within the study area, the EI, GVI, and SSI indicated minimal spatial variance in street vitality.

4. Discussion

4.1. Spatial and Temporal Distributions of Street Vitality

This study revealed a distinct, single-center spatial pattern of street vitality within the old city of Nanjing, China. Vitality was highest in streets near the primary urban center, Xinjiekou, and there was a clear clustering effect, suggesting that high vitality in one area can positively influence the vitality of neighboring regions. The concentration of commercial and office spaces around Xinjiekou draws substantial foot traffic for diverse activities, intensifying street vitality and establishing Nanjing's central activity zone. A comparison of working day and weekend vitality measurements revealed that the tertiary business districts of Hunan Road and Fuzimiao and the quaternary business districts of Ruijin Road and Zhongyangmen had higher vitality than other areas on weekends, underscoring the significance of CL in influencing street vitality during weekend periods. Furthermore, vitality on weekends was more unpredictable than on working days, indicating greater diversity in public activities during weekends.

4.2. Factors Influencing Street Vitality

Overall, FD, TL, and RAR were positively correlated with enhanced street vitality. Streets endowed with ample amenities, prime positioning, and accessible commuting options typically offer a higher caliber of services, thereby attracting more residents and leading to greater vitality, as indicated in previous research [23,27,29,30,36]. FD was strongly associated with street vitality and was more concentrated on working days and more scattered on weekends, possibly due to the more routine nature of resident activities on working days as opposed to weekends [62]. In the proximity of very few large entities and parks, FD was negatively associated with street vitality. This association can be attributed to the stable pedestrian traffic in large built establishments, and expansive parks draw substantial crowds to adjacent zones, resulting in pronounced vitality, albeit with a typically limited number of POIs. TL had a significant positive impact on street vitality generally, and on working days this impact was evenly distributed within the study area, while on weekends only areas near business districts and some metro stations exhibited a positive impact, suggesting that residents have a greater preference for commercial services on weekends. The negative impact of TL on street vitality was particularly pronounced around Zhongyangmen and Sanpailou on weekends, possibly due to the large bus terminal and wholesale market near the central gate, attracting a large number of people even though these areas are some distance from the metro stations in the study area. In addition, the established residential community in the Sanpailou area was serviced by comprehensive amenities, diminishing its reliance on metro stations.

The SSI emerged as a strong correlate of street vitality, indicating that streets capable of delivering superior services hold greater appeal for residents. Recent research has demonstrated that residents' evaluations of their experiences significantly influence waterfront vitality [42]. The regression coefficient for this index was particularly high on weekends, indicating that residents have a higher demand for service quality during their leisure time. Previous studies have noted that higher visual complexity equates to a richer visual experience, enhancing the likelihood of lingering [39,40]. VCI was positively correlated with street vitality, indicating that visually diverse streets are more enticing to residents. RD was positively correlated with street vitality, and this association was more pronounced on working days than on weekends. The same relationship was observed for TL and RAR, indicating that commuting activities are significant indicators of street vitality [66]. Under the time constraints of working days, residents preferred streets that facilitated easy commuting, as per previous research findings [34,37]. The MGWR findings showed that EI was positively associated with street vitality on working days and weekends, perhaps because a higher degree of enclosure facilitates certain social activities that require a sense of bounded privacy, thereby attracting residents to linger and engage in the area [57].

Research on the association between CL and street vitality has been relatively limited, and the majority of findings suggest that streets closer to business districts possess higher vitality [31,32]. The present study showed that CL was positively associated with street vitality on weekends and negatively associated with street vitality on working days. People may be more inclined to spend their weekend leisure time in commercial areas when they have more time and energy to utilize the commercial services [66], whereas on working days, they likely opt for neighborhood businesses or online shopping to meet their basic needs. This finding reflects the diversity of residents' shopping and consumption choices.

FM was positively correlated with street vitality on working days but was not correlated with street vitality on weekends, suggesting that residents prefer streets with diverse functions when leisure time is limited. Given that this study encompasses both the street and its surrounding areas, the increased presence of residents in residential areas on weekends compared to working days may render the influence of this metric on vitality less pronounced [67].

The observation that GVI was negatively correlated with street activity differs from previous studies [38,39]. There are two potential reasons for this phenomenon: (1) Pertinent research indicates that a GVI of 15% represents a threshold in residents' perceptions of urban greening and that beyond this point, urban greening enhances the psychological and physiological well-being of residents [68]. Once the GVI surpasses this threshold, the correlation between the extent of greening and its advantages assumes an "inverted U-shape," with approximately 24% being optimal for resident well-being [69]. In the present study, the average GVI in the old city of Nanjing was 23.58%, with 66.84% of the grids exceeding 15% and 42.25% exceeding 24%, suggesting that urban greening in the old city of Nanjing is quite advanced and that the GVI is not a primary driver of residents' selection of streets for activities. (2) An overabundance of urban greenery might constrict informal commercial spaces, such as the street economy, thereby diminishing street vitality [70,71]. (3) Streets with high GVI require more resources for maintenance and management. If poorly managed, this may result in cluttered green areas, which, in turn, can affect the aesthetics and the experience of using the street [72].

Additionally, PR was not strongly associated with street vitality, contrasting with an earlier empirical study in Osaka which found that permeability along the street interface positively impacted pedestrian activity [13]. However, that study focused on areas adjacent to commercial complexes, whereas our research encompassed streets across the old city without differentiating between street types. Consequently, we suggest that permeability only affects the vitality of streets of a commercial nature.

4.3. Strategies for Enhancing Street Vitality

As forerunners in modernization efforts, old cities should seize the opportunities presented by urban renewal to enhance street vitality and urban spatial quality, thereby meeting the diverse needs of residents. Strategies to enhance street vitality should be approached in a number of ways.

Firstly, increasing functional density is crucial. The attractiveness of streets can be significantly enhanced by adding a wide range of facilities such as dining, retail, entertainment, and cultural facilities, particularly in areas with high pedestrian flow. The flexible utilization of vacant buildings and sites to create temporary markets, exhibitions, and event spaces can also increase street vitality. Furthermore, street vitality can be enhanced by increasing the number of mixed-use neighborhoods that offer a variety of services and activities, especially in areas with high weekday pedestrian traffic.

Secondly, urban planning should draw inspiration from the principles of New Urbanism [16,17] by employing a transit-oriented development (TOD) model to bolster the construction of rail transit stations. Such a model advocates for compact development, integrating mixed functions with small block construction and dense road networks [33,34]. This approach aims to reorganize street and alley spaces to enhance the connectivity and accessibility of street networks, create social interaction spaces on the streets, and improve traffic efficiency. Additionally, in neighborhoods farther away from metro stations, the focus is on the improvement of facilities to neutralize the negative impacts of traffic locations.

Thirdly, while promoting the prosperous development of the city center (such as Xinjiekou), this approach should also stimulate the growth of other commercial centers at various levels. The construction of a multi-tiered, systematic commercial service facility system is proposed to meet the diverse needs of residents and foster social interactions within the region. Simultaneously, by increasing street furniture and vignettes and encouraging diversified architectural designs, the visual complexity of streets can be increased, thus enhancing vitality.

Fourthly, appropriate street greenery is conducive to street vitality, supporting the development of the street economy and promoting related commercial policies. However, it is important to moderate street greening to ensure sufficient space for street-level commerce.

Finally, focusing on residents' subjective experiences is beneficial for human-centered planning. Thus, construction of urban street facilities should meet qualitative as well as quantitative targets. To ensure the adequacy of facility numbers, service quality should be gradually enhanced. A feedback mechanism for residents should be established to improve services in a timely manner and enhance user experience. The goal is to build a city with a "sense of warmth", thereby strengthening residents' sense of belonging.

4.4. Limitations

Although we conducted an in-depth study on street vitality and its influencing factors, this study has several limitations. Firstly, the concept of vitality was initially intricate and expansive. Street vitality, as referenced herein, encompasses both the street's inherent vibrancy and that of its contiguous lands, and the vitality of adjacent areas may affect indicators such as FM. Secondly, the Tencent EasyGo data used in the study do not delineate pedestrian pathways. In addition, situations in which children or other vulnerable groups do not use the Internet services provided by Tencent were not considered. It is recommended that further research on this topic involves integration of data from diverse sources, including heat maps, mobile phones, and social media check-ins. Where possible, field research methods should be incorporated to obtain comprehensive vitality measurements. Moreover, in Section 4.2, we speculate that the influence of GVI on street vitality shows an "inverted U-shaped" relationship, and that PR only influences the vitality of streets of a commercial nature. These speculations need to be explored further. Lastly, the SAM and MGWR models used in this study also have some limitations. The results of the SAM can only reveal the extent of the independent effects of factors on street vitality, and future studies may consider using a geographical detector model to explore the comprehensive effects of different combinations of factors. Although the MGWR model can reveal the spatial heterogeneity of street vitality, it also varies temporally. Therefore, combined with more temporal data, the geographically and temporally weighted regression (GTWR) model is required to obtain a comprehensive analysis of the temporal changes in street vitality.

5. Conclusions

To gain a comprehensive understanding of the characteristics, influencing factors, and enhancement of street vitality in an old city, this study applied a refined scale of analysis, using smaller grid units than previous studies and high-resolution RTUDs to achieve a detailed measurement of street vitality. A more comprehensive set of influencing factor variables was selected from the perspectives of three categories: locational conditions, built environment, and residents' perceptions. Additionally, the SEM and MGWR models were employed to ascertain the factors associated with street vitality and their complex spatial differences.

Several conclusions were drawn from this study. Firstly, street vitality in the old city of Nanjing is monocentric during both working days and weekends, with high vitality areas focused around Xinjiekou, and with greater regularity and predictability in street vitality on working days than on weekends. Secondly, factors such as TL, RD, FD, FM, RAR, EI, VCI, and SSI are positively associated with street vitality. Among them, the association of TL and RAR with street vitality was more pronounced on working days, whereas FD and SSI were more strongly associated with street vitality on weekends. Thirdly, GVI has a negative impact on street vitality, which may be due to the fact that the green environment of streets in the old city of Nanjing has reached a high level, and GVI is not the primary factor affecting residents' choice of streets for their activities. Fourthly, because CL has a positive impact on street vitality on weekends and shows the opposite result on working days, a big difference is observed between residents' shopping demands on working days and on weekends. Therefore, it is necessary to build a multi-level and systematic commercial service facility system. Finally, the influence of different factors on street vitality varied according to spatial location; TL was most strongly associated with street vitality in the southern part of the old city, while FD was most strongly associated with street vitality in the Xinjiekou area.

In summary, against the backdrop of urban development transitioning from expansion to intensification, policymakers and urban planners should recognize the significant role of old city streets in urban spaces. Comprehensive revitalization of the vitality of old city streets can be achieved by adopting a public transportation-oriented development model and constructing mixed-use, compact neighborhoods with dense street networks, ensuring appropriate street greening to support the street economy, and enhancing the quality of urban street service facilities, thereby promoting high-quality urban development.

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