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Research on the Mechanism of Built Environment Affecting Commercial Vitality Mediated by EV Charging Stations: A Case Study of the Main Urban Area of Wuhan

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Abstract

The impact of electric vehicle (EV) charging stations on sustainable urban transitions has become a crucial research topic due to the rapid growth of the new energy industry. However, the uneven distribution of EV charging infrastructure currently presents a major challenge to urban spatial equity and sustainable development. This study focuses on the central metropolitan area of Wuhan, positioning EV charging stations as a key mediating variable to explore how green infrastructure interacts with the built environment to drive sustainable economic vitality. Utilizing multi-source big data, the XGBoost-SHAP model, and Bootstrap mediation tests, this research identifies the non-linear thresholds and mediation pathways involved. The findings reveal that: (1) distinct built environment factors exhibit clear non-linear relationships with commercial vitality; (2) EV charging stations act as critical mediators that spatially reinforce or balance built environment variables, exhibiting pronounced spatial heterogeneity; and (3) EV charging stations show a significant partial mediation effect, with building density wielding the strongest direct influence. This study provides vital scientific support for low-carbon urban planning and sustainable infrastructure deployment by uncovering the threshold characteristics and mediating mechanisms necessary to harmonize commercial vitality with environmental and urban sustainability.

Keywords: multi-source data; EV charging station; commercial vitality; built environment; XGBoost-SHAP; bootstrap mediation analysis; low-carbon transportation

1. Introduction

With the rapid development of cities worldwide, urban vitality has become a core indicator for measuring a city's capacity for sustainable development [1]. One of the most important strategic decisions in the pursuit of a low-carbon and green transition is the creation of new energy vehicles. Governments all over the world have embraced new energy vehicles as an efficient low-carbon mode of transportation; their benefits in reducing carbon emissions and their role in promoting industrial upgrading have been officially recognized as a key strategic direction for the high-quality development of China's economy [2]. Lagging infrastructure is still a major problem, though. The development of the new energy vehicle industry, as described in the "New Energy Vehicle Industry development Plan (2021–2035)," and the improvement of commercial vitality are both impacted by the scientific planning of EV charging station layouts as essential supply facilities [3].

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According to current studies, the built environment has an impact on EV charging station layouts, which in turn have an impact on commercial vitality. In terms of how the built environment affects EV charging station layout, urban road network density [4], elements like infrastructure and land use [5], and spatial layout change how EV charging station facilities are arranged spatially [6]. The need for EV charging for new energy vehicles is segmented by different geographical layouts [7], which also affect consumers' choices for electricity consumption [8] and worsen the unequal distribution of urban resources [9]. In terms of how EV charging station layout affects commercial vitality, EV charging stations create spatial clustering [10] by improving accessibility and operating efficiency through strategic placement, which leads to spatial polarization between "hotspots" and "cold spots" [11]. The concentration of foot traffic in hotspots is further fueled by this polarization effect, greatly increasing the commercial vibrancy of these regions [12]. In terms of how the built environment affects commercial vitality, variations in the built environment across different areas lead to variations in the degree of business clustering and the spatial carrying capacity of infrastructure, which causes commercial vitality to exhibit distinct spatial variations in intensity [13]. Therefore, examining the relationship between the built environment, EV charging station architecture, and commercial vitality has important theoretical and practical implications for improving the efficiency of commercial facilities and optimizing urban spatial structures.

The "built environment–EV charging stations–commercial vitality" interaction mechanism is theoretically based on retail gravity theory, consumer behavior theory, and business format synergy theory. The built environment is the focus of retail gravity theory, which notes that commercial attractiveness is positively correlated with the radius of customer flow and negatively correlated with distance [14]. The layout of EV charging stations is the focus of consumer behavior theory, which emphasizes that a rational layout can create a "EV charging + consumption" model, linking travel with consumption [15]. The theory of business format synergy, which focuses on commercial vitality, asserts that EV charging stations can synergize with nearby business formats to reinforce agglomeration effects and thereby enhance commercial vitality [16].

There is a dearth of non-linear and route mediation analyses in the current academic research on EV charging station facilities, which mostly focuses on building multi-dimensional assessment indicator systems to thoroughly examine related factors [17]. Early research measured the distribution scale of building footprints, nighttime lighting, property prices, and different infrastructure POI data [18], computed coverage, floor area ratio, road network accessibility, regional economic vitality, and purchasing power levels [19], and built conventional linear models to investigate how each dimension affected the design of EV charging stations. As research has progressed, existing studies have utilised multi-source big data to capture the relationship between population activity and commercial vitality [20], and have proposed reasonable indicators of commercial vitality [21]. A variety of machine learning techniques have been introduced into the relevant domains in order to precisely capture these complex nonlinear features. While the Adaptive Neuro-Fuzzy Inference System (ANFIS) model incorporates fuzzy logic and exhibits strong interpretability [22], it is susceptible to the "curse of dimensionality" when handling big data in high-dimensional spaces. In contrast, backpropagation (BP) neural networks have strong non-linear mapping capabilities but suffer from "black-box" limitations and are prone to getting stuck in local optima [23]. By employing the Extreme Gradient Boosting (XGBoost) model and the Shapley Additive Explanation (SHAP) method, these studies have effectively revealed the threshold effects and spatial correlations between different built environments and commercial vitality [24]. Specifically, the SHAP approach in conjunction with machine learning improves the interpretability of prediction models and makes it easier to analyze

non-linear correlations between important variables. The "built environment–EV charging station–commercial vitality" mediation pathway's underlying processes, however, have not yet been thoroughly examined. The majority of current research looks at the connections between the built environment and EV charging station layout, the built environment and commercial vitality, and the layout of EV charging stations and commercial vitality from a single perspective. As a result, the mechanisms and channel connecting the "built environment–EV charging stations–commercial vitality" are still unknown, ignoring the non-linear synergistic impacts of several elements, the quantification of these effects, and the empirical testing of mediation pathways.

Using multi-source big data, XGBoost-SHAP, and a Bootstrap mediation model, this study creates an analytical framework for "built environment—EV charging stations—commercial vitality." The following are the main contributions: (1) It shows how the built environment affects commercial vitality in a nonlinear way and how EV charging stations interact with different built environment variables by acting as a mediator; (2) It identifies important thresholds and spatial heterogeneity in the distribution of EV charging stations within Wuhan's central urban area and suggests typology-based planning recommendations for EV charging stations; (3) Provides a reusable quantitative paradigm for cooperative research on urban green infrastructure and commercial spaces and fills a research vacuum in associative mechanisms and path analysis across the three variables by demonstrating how EV charging stations function as a transmission medium.

2. Materials and Methods

2.1. Study Area

The area under study in this paper is Wuhan City, Hubei Province, China. As the provincial capital of Hubei, a national central city and a megacity, it covers a total land area of 8569.15 square kilometres and is administratively divided into 13 districts, of which the main urban area (central urban area) comprises Jiang'an District, Jianghan District, Qiaokou District, Hanyang District, Wuchang District, Qingshan District and Hongshan District (Figure 1). The central urban area is the region of Wuhan with the highest population concentration, the most dynamic economic activity and the greatest concentration of urban functions. It features high building density and a concentration of commercial service facilities and public infrastructure. At the same time, as China's largest inland high-density city serving as a comprehensive land, water and air transport hub, it has a dense road network but uneven spatial distribution. While transport accessibility is extremely high in core commercial districts and transport hub areas, transport infrastructure in peripheral areas is relatively underdeveloped. This spatial heterogeneity between the built environment and the transport environment has led to inequalities in the distribution of EV charging station facilities within Wuhan's central urban area [25].

2.2. Data Sources and Data Processing

2.2.1. Data Collection

The data selected for this study, as detailed in Table 1, was primarily sourced from various open platforms, with all data points collected in 2024. It covers three core variables: the built environment, EV charging station distribution, and commercial vitality. Based on the different scales outlined in Table 2, the data was categorised into six types to construct the research database.

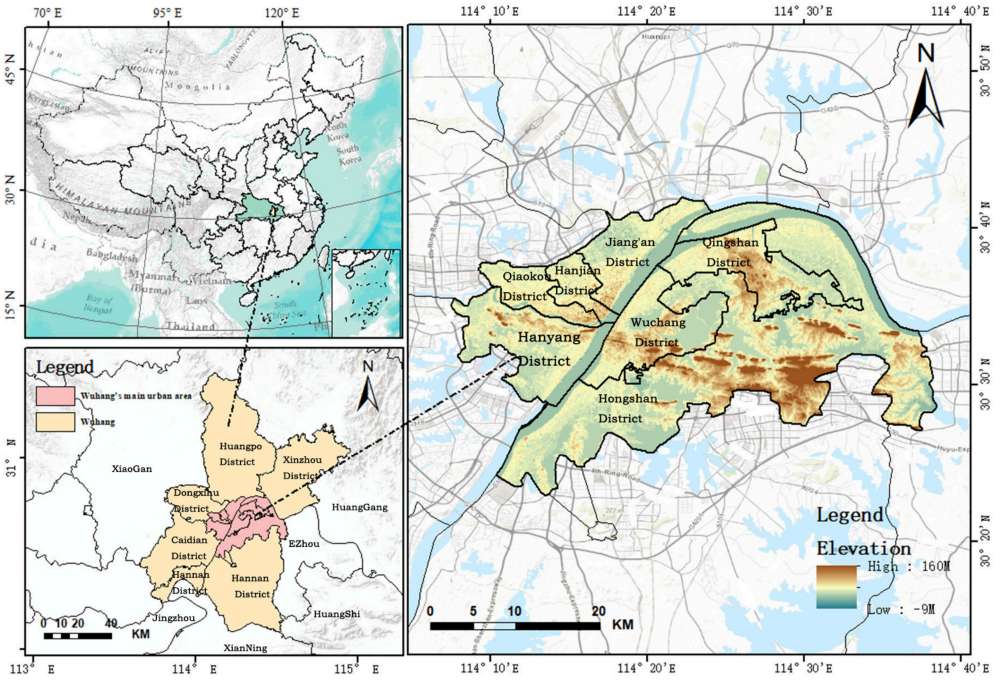


Figure 1. Study location and delineation of the study area.

Table 1. Research Data Information.

Number	Data Name	Year	Resolution	Data Format	Data Source
1	Population density	2024	100 M	Grid	Global Population Distribution Dataset https://www.worldpop.org/ (accessed on 18 October 2025)
2	Building outline	2024	500 M	Vector	National Geographic Information Public Service Platform "Tianditu" https://www.tianditu.gov.cn/ (accessed on 18 October 2025)
3	Road network	2024	500 M	Vector	OpenStreetMap open-source mapping platform https://www.openstreetmap.org/ (accessed on 20 October 2025)
4	Infrastructure Point of Interest (POI) data	2024	500 M	Vector	Amap Open Platform https://lbs.amap.com/ (accessed on 19 October 2025)
5	Population Heatmap	2024	500 M	Vector	Amap Open Platform https://lbs.amap.com/ (accessed on 20 October 2025)
6	Night-time lighting	2024	500 M	Grid	NPP-VIIRS remote sensing imagery https://eogdata.mines.edu/products/vnl/ (accessed on 21 October 2025)
7	House prices	2024	500 M	Grid	Lianjia Property Search Platform https://www.lianjia.com/ (accessed on 18 October 2025)
8	Business Review	2024	500 M	Vector	Dianping.com https://www.dianping.com/ (accessed on 21 October 2025)

Table 2. Research Databases.

Category	Indicators	Formula	Reasons for Choosing
Density	Population density	Total population within the grid/Grid area	By establishing a baseline for EV charging station demand and determining the feasibility of the layout, the synergy between these two factors can minimise the impact of spatial constraints [26].
	Building density	Total floor area of buildings within the grid/Grid area	
Diversity	Scale of facilities at scenic Scale of commercial facilities Scale of residential facilities Scale of public service facilities	Number of POIs for various types of facilities within a grid/Grid area	These four types of facilities provide a relatively comprehensive indication of a region's spatial carrying capacity and potential for population concentration; their distribution and scale directly influence the layout requirements for EV charging stations and the customer base for commercial activities [27].
Spatial layout of EV charging station infrastructure	Scale of EV charging stations	Number of POIs for various types of facilities within a grid/Grid area	Directly characterizes the regional electric vehicle EV charging capacity and density of EV charging stations [28].
Achievable objectives	Scale of transport infrastructure	Number of POIs for various types of facilities within a grid/Grid area	This reflects the level of transportation infrastructure in the area and the accessibility conditions that affect the convenience of using EV charging stations and commercial foot traffic [29].
Design	Road between	$C_{B(i)} = \sum_{j<k} \frac{g_{jk}(i)}{g_{jk}}$ in the equation: g_{jk} represents the number of shortest paths from j to k $g_{jk}(i)$ represents the number of shortest paths passing through	reflecting the traffic throughput capacity of the road and the radiating influence of the commercial area's vitality [30].
	Road centrality	$C_{C(i)} = \frac{1}{\sum_j d_{ij}} d_{ij}$ in the equation: d_{ij} represent shortest distance from i to j	
	Road network density	Total length of roads within the grid/Grid area	
Spatial Perception and Vitality Attributes	Popularity in the Beauty Industry Popularity in the food and drink industry Popularity in the hospitality industry Popularity in the leisure sector	Total number of positive reviews for all service businesses within the grid/Number of businesses within the grid	User engagement metrics provide a clear indication of user traffic and customer satisfaction in commercial settings, and EV charging station deployments are often concentrated in areas with high industry density, such as commercial centers and transportation hubs [31]. The first two indicators accurately capture the spatiotemporal variations and activity levels of population mobility within a region, indirectly reflecting the intensity of commercial and economic activity, while housing prices reflect a region's development potential and consumer spending power [32].
	level of activity among the population on weekdays level of activity among the public on days off	Population heat map values within the grid/Time	
	House price levels	Total property value within the grid/Number of properties	

2.2.2. Data Processing

ArcGIS software (version 10.8) was utilized in this study to grid the study region. It was discovered that the 500 m × 500 m grid achieved the best balance between information retention and computational load by analyzing the spatial variation features across 200 m,

500 m, and 1000 m grids. Consequently, 5489 grid cells of 500 m by 500 m were meticulously constructed from the research area. All multi-source data was uniformly reprojected into a projected coordinate system prior to being imported into ArcGIS. Business vitality was analyzed using an entropy-weighted method, and spatial connectivity was used to correctly count and resample data points such POIs, property values, and contours into a 500 m grid. Extreme outliers were consistently eliminated from every feature, and normalization was carried out to complete the cross-platform, multi-source data processing. This produced a fully covered grid analysis system, laying the foundation for next statistical modeling and machine learning-based spatial analysis.

2.3. Research Methodology

As shown in Figure 2, this study created a research paradigm that incorporates "built environment—EV charging station distribution—commercial vitality." The methodology used in this part is based on the following logic: "dataset construction—feature modeling—correlation analysis—non-linear identification—mediation testing." To construct an indicator system for the built environment, EV charging stations, and commercial vitality, multi-source data is first standardized at a grid resolution of 500 m; redundant variables are then removed using Lasso and Spearman's correlation. Second, the XGBoost-SHAP model addresses the shortcomings of conventional linear models in capturing intricate correlations by examining non-linear relationships, thresholds, and interaction effects across variables while examining their spatial heterogeneity. Lastly, the Bootstrap method is used to examine the mediating effect of EV charging stations, and two-stage least squares and instrumental variables are used to rule out reverse causality. This thorough approach may successfully explain the transmission mechanism between the built environment, EV charging stations, and commercial vitality. It provides a whole line of reasoning, from geographical feature analysis to mechanism identification and causal confirmation.

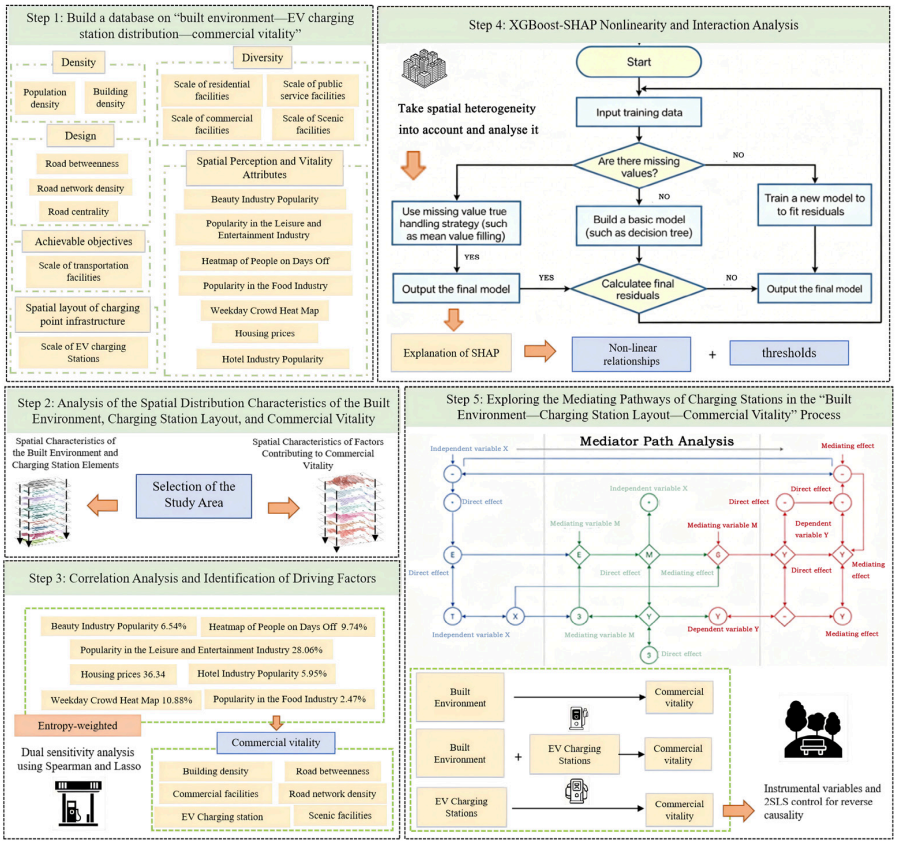


Figure 2. Experimental flowchart.

(1) XGBoost and the SHAP Model

Based on gradient-boosted decision trees, XGBoost is an ensemble learning technique that can effectively match intricate nonlinear patterns and variable interaction effects [32]. It improves the model's interpretability with respect to both local and global feature relevance as well as the interaction effects among model features when paired with the SHAP interpretability framework [33]. This illustrates the general association between particular features and prediction results and is somewhat modified by the particular values of feature parameters [34]. This study uses the XGBoost machine learning model for nonlinear regression analysis to solve the limitations of thresholds and saturation effects in previous evaluation systems. Its main benefit is that it automatically handles missing information and controls model complexity with regularization terms to prevent overfitting; in terms of predicted accuracy, it usually performs better than conventional linear models.

Commercial vitality intensity is the prediction target in this study, which trains the model by maximizing the objective function using all built environment spatial variables and EV charging station density as input characteristics. Finding an ideal model function f that minimizes the total objective function—which takes prediction loss and model complexity into account—is the aim of the XGBoost model. The following is an expression for the objective function *Obj*:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

Here, n is the number of samples, $l(y_i, \hat{y}_i)$ is a loss function that measures the discrepancy between the model's predicted value $\hat{y}_i$ and the true value y_i (such as mean squared error), K is the total number of trees, and $\Omega(f_k)$ is the complexity penalty term for the kth tree, used to control the model's complexity.

For a specific prediction sample, its predicted value $f(x)$ can be decomposed into the sum of the baseline value (the average of predictions across all samples) and the SHAP values of each feature:

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i \quad (2)$$

Here, ϕ_0 is the baseline value, and ϕ_i is the SHAP value for the i-th feature. A positive SHAP value indicates that the feature has a positive impact on the current prediction; a negative value indicates a negative impact. The SHAP value's absolute value indicates the strength of the feature vector's influence on the prediction target, while its sign indicates the direction of that influence.

(2) Mediation Model

The Bootstrap mediation analysis method was also used for testing in this study. One of the most popular and commonly used techniques for dealing with mediation and moderation effects is bootstrap mediation analysis, which has the benefit of not requiring the product of coefficients to have a normal distribution [35]. We can draw strong statistical conclusions about the importance of the indirect impact of EV charging stations on the relationship between the built environment and commercial vitality by creating confidence intervals for the mediation effect values through repeated sampling with replacement (set at 5000 samples in this study). Determining the statistical significance of the indirect effect that the independent variable (X) has on the dependent variable (Y) through the mediat-

ing variable (M) is the fundamental component of mediation analysis. Three regression equations make up the fundamental model:

$$\begin{aligned} Y &= cX + e_1 \text{ (General Effects Model)} \\ M &= aX + e_2 \text{ (Path } a\text{)} \\ Y &= c'X + bM + e_3 \text{ (Direct effects and Pathb)} \end{aligned} \tag{3}$$

In this context, the product of the coefficients $a \times b$ represents the mediating effect, and the total effect c is equal to the sum of the direct effect c' and the mediating effect $a \times b$. The bootstrap method involves repeatedly sampling a large number of samples with replacement from the original sample and calculating the mediation effect values $a_i \times b_i$ in each bootstrap sample to obtain an empirical distribution. This reveals the intrinsic transmission pathways through which built environment factors influence the layout of EV charging stations and, in turn, affect commercial vitality.

3. Results

3.1. Spatial Distribution Characteristics

In terms of the spatial distribution of the built environment and EV charging stations (as shown in Figure 3), areas with high building density and high POI density for commercial and service facilities are highly concentrated in the Jianghan Road–Wuguang Business District of the Hankou core area and the Chu River Han Street–Shuiguohu section of the Wuchang core area. Meanwhile, areas with high POI density for transportation service facilities are primarily distributed around railway hubs such as Hankou Station and Wuchang Station, as well as along cross-river corridors. Areas with high POI density for EV charging stations align closely with the Optics Valley Science and Technology Innovation Corridor, the Jianghan Road business district, and the Hankou Station hub area. As elements of the built environment where elements are concentrated and EV charging demand is high, core business districts and transportation hubs are highly spatially coupled.

Figure 4 indicates that areas of high commercial vitality are highly concentrated in the Jianghan Road–Wuguang Business District and the Chu River Han Street–Optics Valley Square areas, exhibiting a "high-center, low-periphery" pattern, and are highly coupled with the high-value zones of various driving factors. The high-value zones of average heat maps on weekdays largely overlap with core business and office districts. On weekends, the high-value zones of average heat maps extend toward consumer-oriented business districts such as Optics Valley Square and Jianghan Road. Areas with high average housing prices are also concentrated in the same sectors, where high purchasing power and commercial value mutually reinforce each other, leading to a high concentration of commercial formats. High-value zones for the food and beverage sector are located in traditional culinary districts such as Jianghan Road and Jiqing Street; high-value zones for the beauty and wellness sector are concentrated in high-end consumption settings like Wuguang and Chuhe-Han Street; high-value zones for the hotel industry correspond to areas surrounding transportation hubs such as Hankou Station and Wuchang Station; and high-value zones for the leisure and entertainment sector align closely with areas where young consumer groups congregate, such as Optics Valley and Jianghan Road.

A comparison of Figures 3 and 4 reveals that areas with high commercial vitality, built environments, and EV charging stations exhibit a high degree of spatial overlap. Areas such as Jianghan Road and Optics Valley are not only high-value zones in terms of building density and commercial service facilities but also dense clusters of EV charging stations, while simultaneously serving as core areas of commercial vitality. There may be a transmission pathway between the "built environment—EV charging stations—commercial vitality" factors.

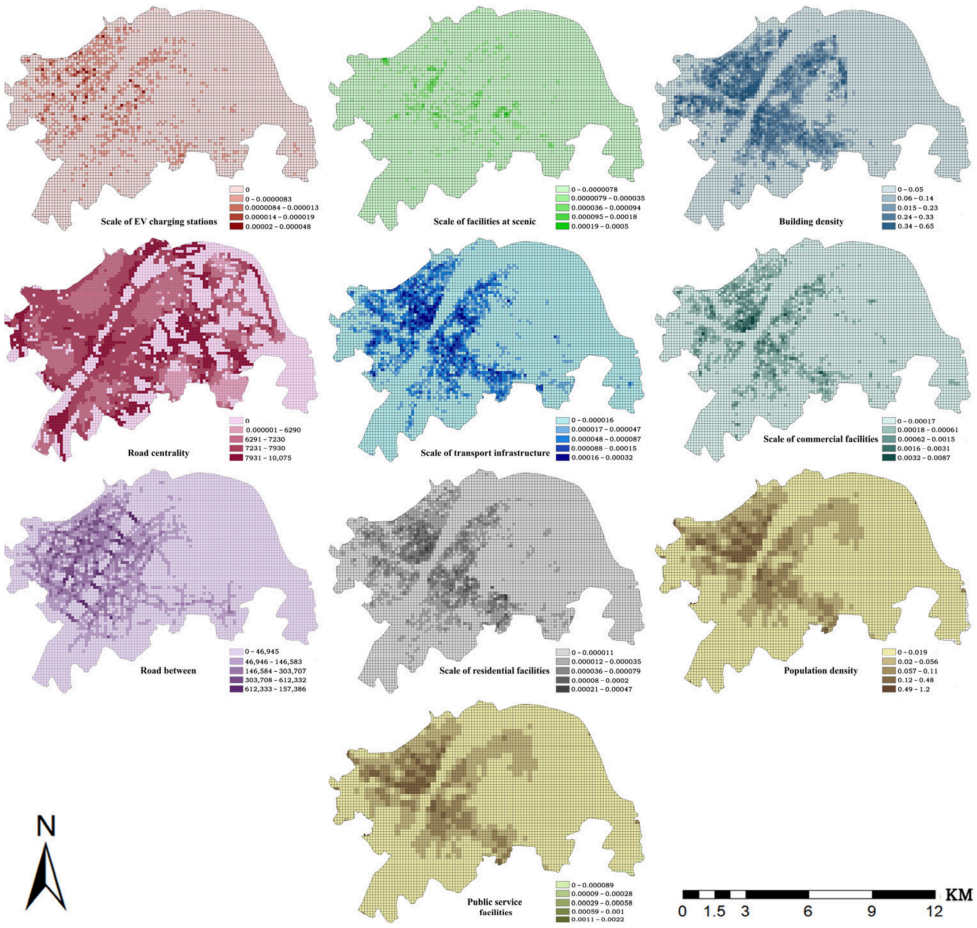


Figure 3. Distribution characteristics of the built environment and EV charging stations.

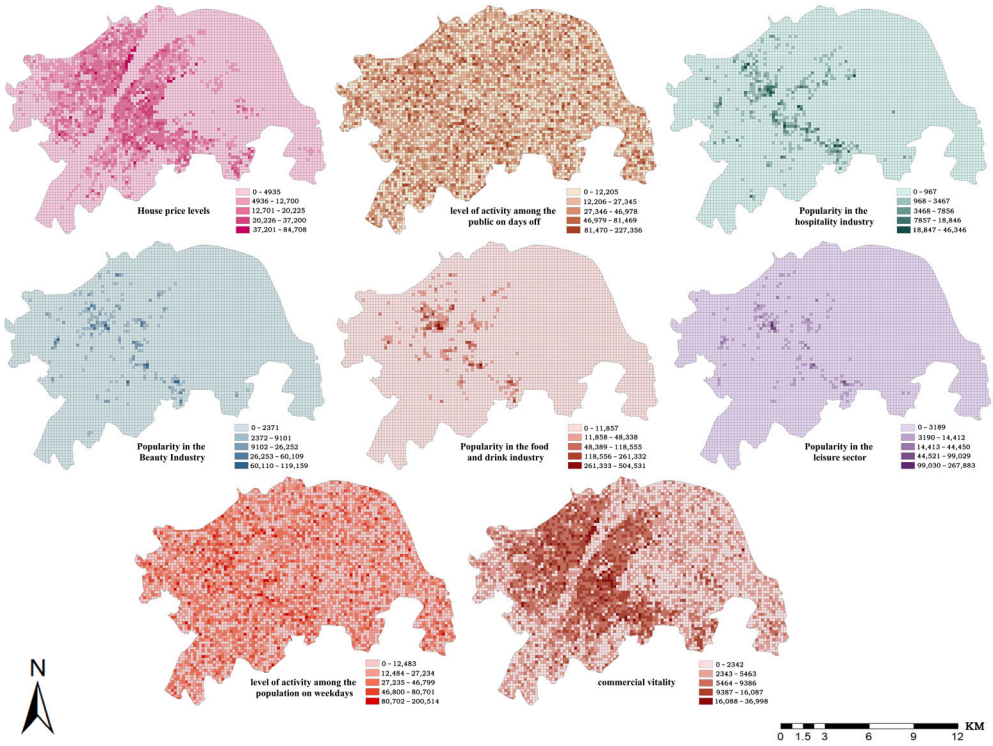


Figure 4. Distribution characteristics of commercial vitality.

3.2. Correlation Analysis

To address the issue of multicollinearity among the variables, this study first employed Spearman's correlation analysis to quantify the strength and direction of the relationships between each variable and commercial vitality. The results are shown in Figure 5. All independent variables are positively correlated with commercial vitality, but the strength of these correlations varies significantly: public service facilities and building density exhibit the strongest positive correlations with commercial vitality, followed by transportation service facilities, residential service facilities, and commercial service facilities, and population density. This naturally and strongly leads to the conclusion that a high-intensity built environment, comprehensive public service facilities, and appropriate population density are the most critical factors underpinning commercial vitality. Complementing this, road betweenness and road network density also exhibit moderate correlations, indicating that an efficient road network structure has a direct positive impact on commercial activities. Finally, EV charging station facilities, scenic facilities, and road proximity all exhibit weak positive correlations with commercial vitality. The correlation between road accessibility and commercial vitality is relatively weak, indicating that its independent explanatory power for commercial vitality is limited in the current model. Although population density shows a certain correlation with variables such as commercial vitality and EV charging station facilities, its Variance Inflation Factor (VIF) value is greater than 10. Considering the high correlations among public service facilities, commercial service facilities, transportation service facilities, and residential service facilities, and to avoid model redundancy, population density, public service facilities, road proximity, transportation service facilities, and residential service facilities were all excluded from subsequent analyses.

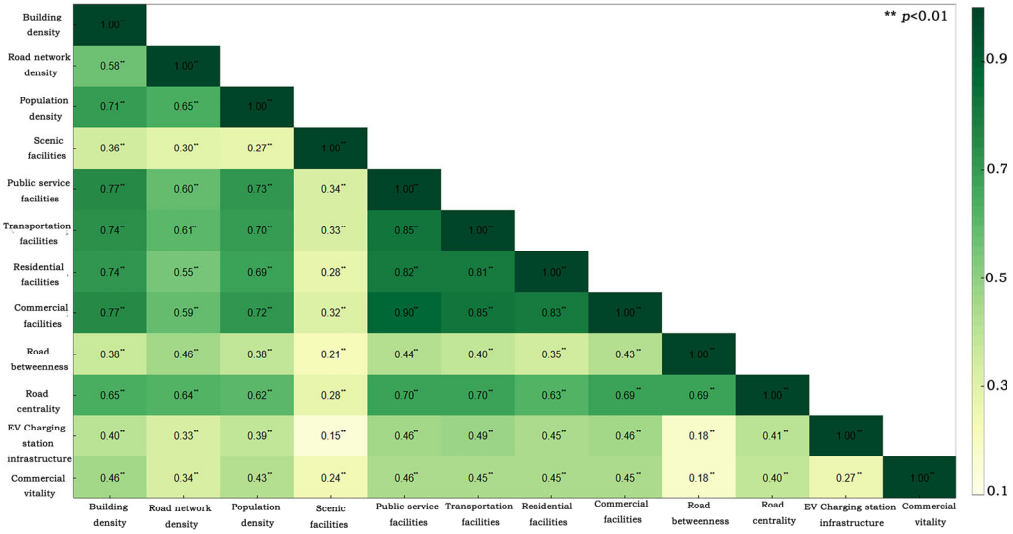


Figure 5. Spearman's correlation analysis results.

This study performs a sensitivity analysis using LASSO regression (Least Absolute Shrinkage and Selection Operator) to verify the validity of variable selection and rule out any model bias (see Figure 6). By adding a regularization term and reassessing the contribution of variables, LASSO regression successfully addresses the problem of multicollinearity. The plot results demonstrate that the regression coefficients for building density, road network density, road intermediation, and commercial service facilities are extremely stable and continuously function as key predictors in the model while the regularization parameter lambda varies. The population density regression coefficient, on the other hand, tends to zero. Even though variables like public service facilities did well in the correlation analysis, during the LASSO variable selection process, their data is mostly

explained by core variables like building density (Figure 5 shows that their correlations are all greater than 0.80), and their coefficients converge quickly, indicating their model redundancy. This result is very consistent with the earlier analysis: eliminating variables with high multicollinearity while keeping essential built environment components not only prevents significant model bias but also enhances the explanatory power of the model and the robustness of parameter estimates, guaranteeing the accuracy of interaction analyses that follow.

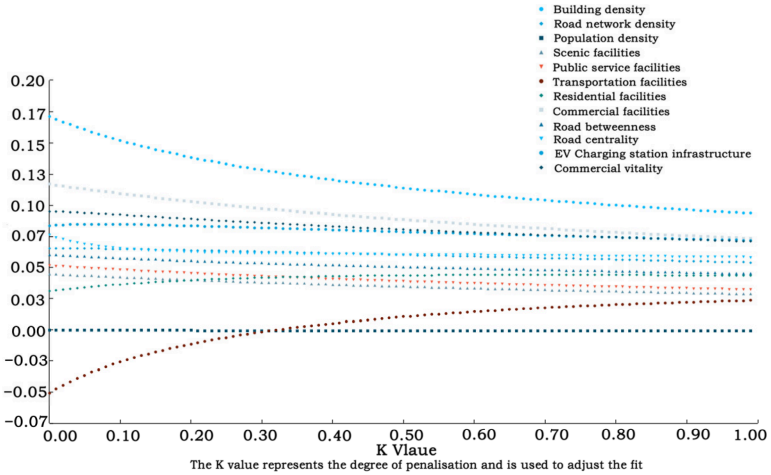


Figure 6. LASSO sensitivity analysis results.

3.3. XGBoost-Shap Analysis

3.3.1. XGBoost Model Performance Evaluation and Validation

To thoroughly investigate the underlying mechanisms, this study conducted a systematic comparative analysis of three candidate models: LightGBM, Random Forest, and XGBoost. During the data preprocessing stage, to objectively evaluate the models' generalization capabilities, the entire dataset was randomly split into training and testing sets in an 8:2 ratio. This was done to examine the mechanisms through which EV charging stations influence commercial vitality in built environments, and XGBoost was ultimately selected as the model for this study.

Subsample reverse sampling stress testing is used in this work to assess the robustness of the model under low-density and anomalous distribution situations, as well as to verify its stability in harsh or sparse data scenarios. The work creates a very sparse dataset by reducing the sample size to 20% of the original dataset, which is subsequently retrained and tested. As shown in Table 3, even under stress circumstances with drastically reduced sample size and extreme sparsity, the XGBoost model outperformed the Random Forest and LightGBM models on the test set under comparable sparsity conditions. This reveals that the XGBoost-SHAP prediction system described in this paper is highly generalizable and noise-resistant in low-density extreme cases.

Table 3. Evaluation Results.

Scene Division	Model Name	R^2	MSE	RMSE	MAE
Full dataset	Random Forest	0.7941	0.0123	0.1109	0.0591
	LightGBM	0.8105	0.0108	0.1039	0.0557
	XGBoost	0.8256	0.0095	0.0975	0.0518
Low-density dataset	Random Forest	0.7412	0.0156	0.1249	0.0684
	LightGBM	0.7658	0.0132	0.1148	0.0612
	XGBoost	0.7842	0.0112	0.1058	0.0545

3.3.2. Nonlinear Contribution Analysis

With an average SHAP value of 0.031, building density contributes the most, as seen in Figure 7, demonstrating the strongest correlation between urban building density and commercial vitality. Road betweenness and commercial service facilities had contribution values of 0.016 and 0.013, respectively. The distribution of commercial service facilities is an essential pillar for the regular operation of urban systems and is evidently substantially connected with urban consumer vitality and service supply capability. Road network density and scenic facilities have average SHAP values of 0.007 and 0.006, respectively, but both are essential for daily life and urban transit, and they undoubtedly contribute to commercial vitality. In terms of commercial vitality, the average SHAP value for EV charging station facilities is about 0.003. Additionally, because of their dispersed location, they are vulnerable to outside intervention, indicating that EV charging stations would not directly and significantly affect commercial vitality but rather serve as a "conduction medium" to indirectly support it.

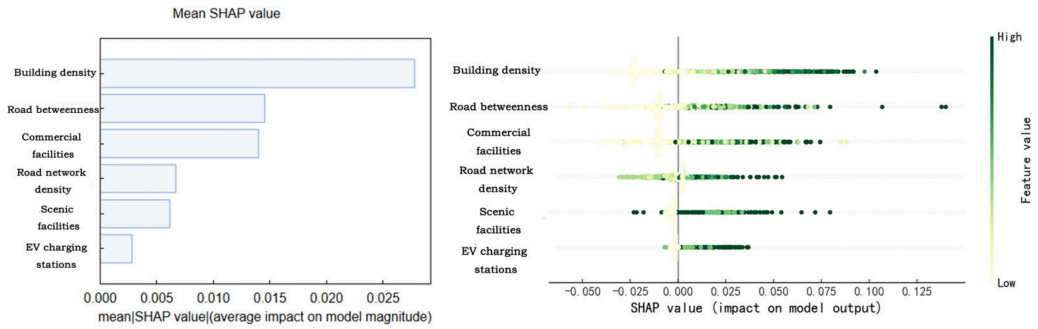


Figure 7. Weighted map of built environment and EV charging station facilities vs. commercial vitality.

All built environment elements' partial dependence curves reveal nonlinear variations, showing distinct threshold effects and diminishing marginal returns, according to the partial dependence plot (PDP, see Figure 8). As density grows from 0.0 to 0.4, commercial vitality steadily increases, reaching a high in the 0.3–0.4 range (about 0.20). This suggests that whereas inadequate spatial aggregation at building densities below 0.2 directly prevents the full realization of facility effectiveness, population and activity aggregation are the main drivers of the target variable when building density surpasses 0.2. The typical feature of "significant gains in the low range and saturated effects in the high range" is also present in the partial dependence curves for road network density and road betweenness: road network density increases steadily in the 0.0–0.10 range and tends to stabilize at 0.13–0.14; road betweenness shows a fluctuating upward trend, peaking in the 0.10–0.15 range (roughly 0.175). This shows that increasing road network coverage and connectivity has a direct positive driving effect on the target variable when road network density and betweenness are less than 0.10. However, once transportation infrastructure matures, it is advised to achieve reasonable synergy with commercial facilities and EV charging stations.

The pattern of "strong driving effect in the low-configuration stage and effect saturation in the high-configuration stage" is seen in the partial dependence curves for EV charging stations, commercial service facilities, and scenic facilities. The density of EV charging station facilities rises quickly from 0.0 to 0.2, peaks at 0.14, and then tends to stabilize; the density of scenic facilities rises quickly from 0.0 to 0.25, peaks at roughly 0.16, and then stabilizes at 0.14; and the density of commercial service facilities rises quickly from 0.0 to 0.02 before remaining stable at 0.13–0.14. Therefore, correcting these deficiencies might significantly boost regional vitality in the early phases while facility coverage is still low (scenic facilities < 0.25, commercial services < 0.02, EV charging stations < 0.2). This

suggests that the driving function of built environment elements is not independent but rather the outcome of the combined effects of "single-factor threshold constraints" and "multi-factor synergistic coupling," when combined with the analysis of interaction effects.

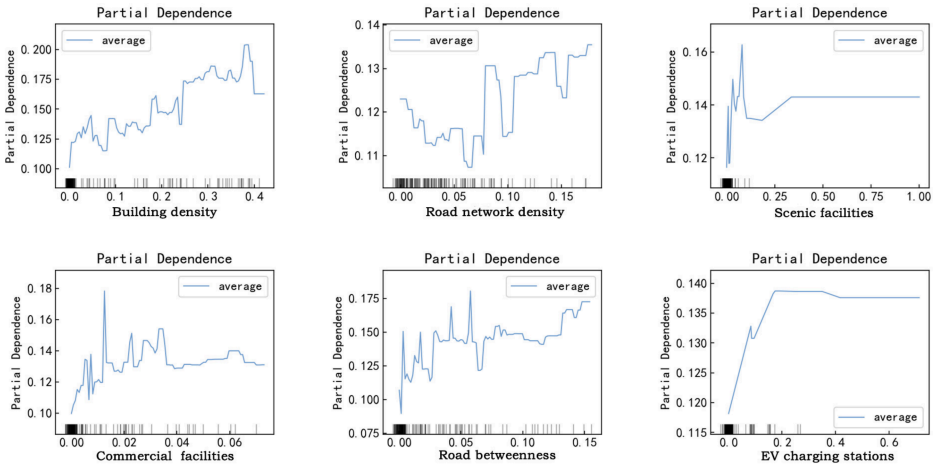


Figure 8. PDP analysis of the built environment and EV charging stations on commercial vitality.

3.3.3. Interaction Analysis

Figure 9 illustrates the complex interrelationships between EV charging stations and the built environment, as well as their combined impacts on commercial vitality. The link between building density and EV charging stations exhibits the greatest range and most pronounced fluctuations in SHAP values. The unique dynamic pattern of "initially positive, then negative" in the relationship between road network density and EV charging station facilities indicates that transportation accessibility acts as a regulatory threshold for facility efficacy. The interaction between road betweenness and EV charging station facilities is focused in the low-intermediation range, with a discernible positive peak for high EV charging station configurations. This suggests that in areas with inadequate road connection, EV charging stations have a clear compensating driving effect. The interaction between commercial service facilities and EV charging stations also manifests as positive variations in areas with limited commercial penetration. In terms of scenic attractions, the interaction shows a significant positive driving effect for the installation of EV charging stations in areas with very low densities of scenic attractions; however, as the coverage of scenic attractions increases, the interaction effect between the two gradually decreases.

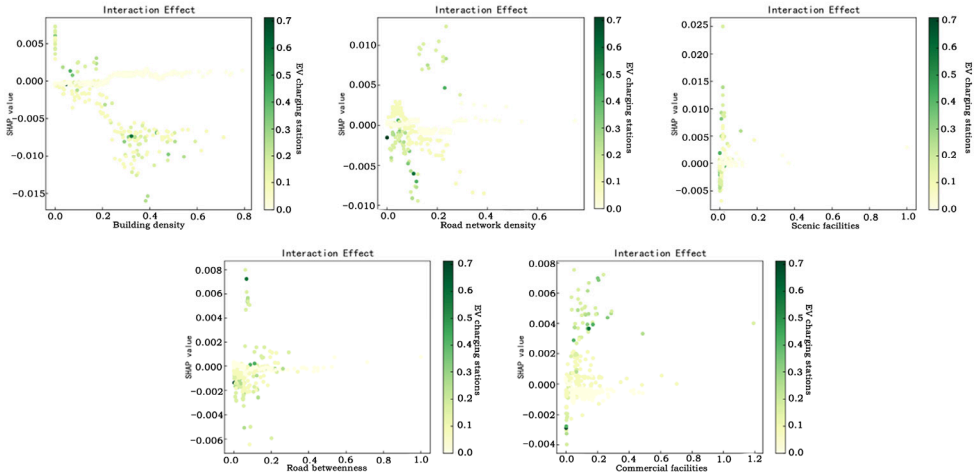


Figure 9. Interaction diagram of the built environment and EV charging station facilities.

A holistic study of these interactions reveals significant threshold characteristics in the synergy between EV charging stations and the built environment. As shown in Figure 8, the interaction between building density and EV charging stations remains predominantly positive in the low-density range but exhibits a sharp decline toward an inhibitory phase once building density reaches approximately 0.20. This suggests that while agglomeration initially benefits vitality, extreme density leads to diminished marginal returns, eventually reaching a saturation point at 0.40. Regarding road network density, the interaction displays an initially positive then negative pattern. The synergistic effect is most pronounced at low density levels near 0.10 and gradually transitions into a negative impact as connectivity increases, indicating a clear saturation threshold. Furthermore, the interactions for road betweenness, commercial services, and scenic attractions are highly sensitive and concentrated in the extremely low-value ranges. These variables all demonstrate distinct threshold reversals, where the initial positive synergy rapidly dissipates and turns into an inhibitory effect as the intensity of the built environment slightly increases beyond the thresholds of 0.10 for road betweenness and 0.05 for commercial services.

3.3.4. Analysis of Spatial Heterogeneity

XGBoost models were fitted independently for the districts of Jiang'an, Jianghan, Qiaokou, Wuchang, Qingshan, Hongshan, and Hanyang in Wuhan's central urban area in order to determine whether there is spatial heterogeneity in the thresholds for the interaction of charging points and the built environment. The results are displayed in Table 4.

Table 4. Threshold Results.

Variable Name	Central	Jianghan	Jiang'an	Qiaokou	Wuchang	Hanyang	Hongshan	Qingshan
Building density	0.21	0.25	0.12	0.15	0.31	0.15	0.42	0.39
Road network density	0.10	0.12	0.12	0.05	0.20	0.05	0.25	0.21
Scenic facilities	0.03	0.05	0.01	0.02	0.02	0.01	0.04	0.05
Commercial facilities	0.09	0.05	0.03	0.03	0.07	0.04	0.12	0.10
Road betweenness	0.11	0.10	0.05	0.05	0.09	0.03	0.14	0.18

The thresholds for the interaction between EV charging stations and built environment variables showed significant spatial variation, according to a heterogeneity test carried out across seven administrative districts in Wuhan. In Jiang'an, Qiaokou, and Hanyang districts, synergistic effects were triggered at extremely low Commercial facilities thresholds, reflecting the high sensitivity of mature commercial districts to increases in infrastructure; Jianghan District's threshold characteristics closely align with those of the wider central urban area, demonstrating robust systemic adaptability; in Hongshan and Qingshan districts, which are emerging development zones or industrial areas undergoing transformation, require a higher concentration of factors to overcome spatial resistance and thereby stimulate commercial vitality.

3.4. Exploration of Mediating Effects

The study found that EV charging station facilities exhibit a high degree of synergy with the built environment and commercial vitality. Areas with high POI density for EV charging station facilities show a high degree of overlap with the built environment and commercial vitality within the same districts. However, the relationship between EV charging station facilities and commercial vitality is weakly positive with a low SHAP value, and there is a moderate positive correlation with some built environment factors. This indicates that while the direct contribution of EV charging stations to commercial vitality is limited, their close synergistic relationship with built environment factors suggests

they likely act as a "conduction medium" mediating the relationship between the built environment and commercial vitality.

To further test the mediating pathway of EV charging station facilities, the Bootstrap mediation analysis method (5000 bootstrap repetitions) was employed to construct a mediation model with built environment factors as independent variables, EV charging station facilities as the mediator, and commercial vitality as the dependent variable (see Figure 10). The total effects model indicates that the direct effects of all built environment factors on commercial vitality are significant ($R^2 = 0.331$), with building density ($\beta = 0.411^{**}$) and commercial service facilities ($\beta = 0.292^{**}$) exhibiting the strongest predictive power. In Path A, with EV charging station facilities as the dependent variable, the results indicate that commercial service facilities ($\beta = 0.322^{*}$) and building density ($\beta = 0.311^{**}$) contribute most significantly to the distribution of EV charging stations, while scenic attractions have a weaker effect ($\beta = 0.029^{**}$). EV charging station facilities showed a significant positive impact on commercial vitality ($\beta = 0.055^{*}$) when both built environment factors and EV charging station facilities were included simultaneously, and the coefficients of all built environment factors decreased, suggesting the existence of a mediating effect. About one-third of the built environment's impact on commercial vitality is achieved through the transmission pathway of EV charging station facilities, according to the study, which found that the mediating effect of these facilities accounted for 33.5% of the total effect.

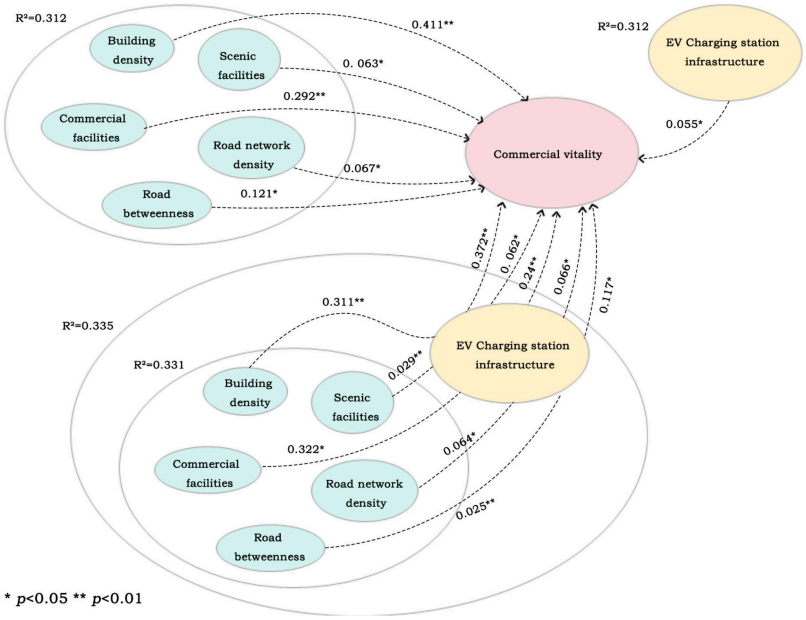


Figure 10. Diagram of the mediating path model.

Three elements summarize the mediating mechanism of EV charging station facilities. First, by mediating the built environment, EV charging station facilities indirectly improve commercial vitality through a positive transmission mechanism. The second is the threshold regulatory mechanism, which places restrictions on EV charging station facilities and demands that the built environment reach a specific threshold before they can play a mediating function. Third, the synergistic enhancement mechanism, in which the built environment exerts a positive promotional effect on EV charging station facilities, which in turn indirectly enhances the commercial vitality of the surrounding area through mediating pathways.

This study uses the instrumental variables causal inference approach to examine the possible inverse causal relationship between EV charging stations and commercial vitality. The Wuhan power grid's 2022 grid load capacity was selected as the instrumental variable

because it satisfies the two primary criteria of exogeneity and correlation. According to the findings of the two-stage least squares (2SLS) regression, there was no weak instrument issue in the first stage, as the grid load capacity regression coefficient on real EV charging station density was 0.372 ($p < 0.001$) with an F-value of 106.27 > 10. The regression coefficient of EV charging station density on commercial vitality was 0.064 ($p < 0.01$) in the second stage, which is near the origin after accounting for reverse causality. This implies that the study's primary conclusions are causally solid and that the partially mediating effect of EV charging stations is still significant even after accounting for reverse causality.

4. Discussion

4.1. Methodological Innovations and Analytical Framework

From the perspective of urban geography, the "synergistic grouping" of significant urban characteristics in geographic space frequently results in multicollinearity issues, making it challenging to accurately ascertain the spatial marginal contributions of these aspects. In order to solve this, we methodologically addressed a problem in a prior study that did not do correlation analyses on data from several sources [36]. To increase the reliability of the results, we eliminated duplicate variables with multicollinearity using a dual sensitivity analysis with Spearman's correlation and LASSO. By developing an integrated analytical framework of "built environment—EV charging station distribution—commercial vitality," this study characterizes EV charging stations as a "spatial transmission medium" in contrast to other research that considered infrastructure as a single spatial factor [37]. We provide quantitative empirical study of the effect pathways using the XGBoost-SHAP machine learning technique in conjunction with Bootstrap mediation tests, going beyond a single regression model. The instrumental variables method enhances the reliability of causal inference. This provides methodological support for urban resilience planning and fills a gap in earlier research on the mediating impacts of infrastructure.

4.2. Nonlinear Thresholds and Spatial Heterogeneity of Built Environment Driving Effects

First, we found that, in line with previous research [38], the built environment has a nonlinear impact on commercial vitality. There are one or more thresholds for each variable when the influence shifts from negative to positive or from positive to negative. For instance, although if it varies, commercial vitality typically shows a synergistic relationship with each variable before Building density reaches 0.4 and Road network density, Scenic facilities, Commercial facilities, and EV charging stations reach 0.15. This suggests that in order to achieve gradual, intensive growth, one should follow threshold patterns rather than mindlessly pursuing the expansion of built elements and EV charging stations in terms of number and scale.

Furthermore, if a certain level is reached, modifications to any one built environment indication might either increase or decrease the impact of EV charging stations, with dire repercussions. For instance, the synergistic boosting effect on EV charging stations changes to an inhibiting effect as Building density gets closer to 0.2. This is in line with earlier studies that discovered that geographical competition or limitations in the power distribution system's (DS) support capacity (PSC) might have detrimental effects on EV charging stations [39]. However, regional heterogeneity was not taken into consideration in the study. Consequently, we performed a geographic heterogeneity analysis in our study and found that EV charging stations and other built environment indicators were more likely to surpass the threshold at which the influence shifts from positive to negative in areas with established commercial districts. For instance, both Jiang'an and Qingshan Districts belong to Wuhan's center urban region based on the city's basic spatial dynamics. However, because of its well-established commercial sector, Jiang'an District is more vulnerable to negative

externalities such traffic congestion, spatial crowding, and inadequate power distribution system capacity due to excessive facility concentration. Therefore, when construction density is lower than in Qingshan District, the marginal benefits of EV charging stations become inhibitory. This demonstrates that developing urban EV charging stations cannot be done in a "one-size-fits-all" manner or solely by increasing the number of EV charging stations. In order to execute a differentiated structure, it should instead develop reference criteria based on regional characteristics, taking into account geographical resource relationships and the capacity of the metropolitan energy distribution system.

4.3. Spatial Mediating and Transmission Mechanisms of EV Charging Stations

EV charging stations have a part in the built environment's influence on commercial vitality, according to the examination of mediating effects. They work in concert to affect things like Building density, Road network density, Road betweenness, Commercial facilities, and Scenic facilities. This is in line with earlier studies that show EV charging stations indirectly boost local companies' spending by attracting consumers [11]. This implies that the mediating impacts of EV charging stations, such as lengthening customer dwell times and offering social and replenishment functions, can affect the local environment by converting fleeting traffic flows into steady pedestrian flows, so boosting commercial vitality. This logic has been validated by pertinent studies and the idea of business format synergy [40]. Because of this, EV charging stations should not be viewed as merely basic supporting infrastructure during planning; rather, their role as a mediator between the built environment and commercial vitality should be emphasized. They can be combined with nearby business formats, Road betweenness, and public service facilities through coordinated planning to continuously reinvigorate neighborhoods' commercial vitality.

4.4. Differentiated Planning Recommendations for EV Charging Infrastructure in Wuhan's Central Urban Area

Drawing from the Wuhan New Energy Vehicle Charging Infrastructure Construction Plan and the Implementation Rules for Subsidies on the Construction and Operation of Electric Vehicle Charging Infrastructure in Wuhan, this study proposes the following recommendations for the EV charging station planning of Wuhan's central urban area: (1) The government should temporarily halt large-scale tendering for EV charging station construction in key commercial districts like Jianghan Road, Wuguang, Chu River Han Street, and Optics Valley Square where Building density exceeds 0.2 and Road network density exceeds 0.1. This will improve transportation and spatial agglomeration and prevent resource waste from premature deployment. According to the policy, Commercial facilities owners should receive operational subsidies equal to 15% of the actual investment in peripheral urban areas like Baishazhou in Hongshan and the southern part of Sixin in Hanyang, where Building density is less than 0.2 and Road network density is less than 0.1. To improve the integration of charging with business settings, a compact, embedded layout should be used. This will fully utilize the beneficial intermediate role of EV charging stations to increase the commercial spillover effects of EV charging stations and extend consumer dwell periods. Subsidize small businesses in compliance with policy requirements to establish a moderate number of tiny, user-friendly EV charging stations in Scenic facilities and ecological places like Donghu and Huanghelou. To increase visitor stay times and foster a connection between ecology and commerce, use EV charging stations. Strengthen supply through integrated energy stations at transportation hubs like Hankou Station, Wuchang Station, and Wuhan Station, as well as in places with weak Commercial facilities. Use EV charging stations as spatial anchors to draw people in and revitalize neighborhood amenities.

5. Conclusions

In order to develop an analytical framework of "built environment—EV charging station distribution—commercial vitality" in Wuhan's central urban area, this study employed XGBoost-SHAP and Bootstrap mediation tests based on multi-source big data. This framework thoroughly examined the mechanism by which the built environment influences commercial vitality through the mediation of EV charging station distribution. The results demonstrate: (1) threshold effects and diminishing returns are present in the impact of different built environment characteristics on commercial vitality; and (2) threshold effects and regional heterogeneity are present in the interactions between these factors and EV charging stations. The central urban area and the various administrative districts were compared as a result, and planning guidance strategies based on various thresholds were suggested; (3) EV charging stations have a relatively small direct effect as a mediator in the built environment's influence on commercial vitality; instead, they play a partial mediating role and produce synergistic effects with all variables within the mediation pathway. These results offer data support and a scientific basis for the coordinated development of urban multifunctional systems and EV charging station planning.

Four limitations and future directions remain, despite the fact that this study systematically reveals the mediating mechanisms and threshold characteristics of EV charging stations: (1) The charging behavior of vulnerable groups and private EV charging stations were not included; user charging preferences may shift from "consumption-oriented" to "safety-oriented," resulting in some sample bias [41]. Future research should concentrate on the effects of extreme weather conditions (EWC) on system interactions; (2) EV charging stations may transmit system disturbances under extreme conditions; (3) the conclusions are based on a single, high-density urban center in Wuhan, so their generalizability is limited; (4) multi-year panel data could be used to test long-term causal relationships via a cross-lagged panel model (CLPM), supplemented by micro-level user survey data. A more robust urban spatial layout model and more accurate decision-making support for the coordinated development of green infrastructure and commercial areas could arise from future research that includes cross-city comparisons to verify the universality of thresholds and mediating effects.

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References

1. Balram, S.; Dragićević, S. Attitudes toward urban green spaces: Integrating questionnaire survey and collaborative GIS techniques to improve attitude measurements. *Landsc. Urban Plan.* **2005**, *71*, 147–162. [CrossRef]
2. Xuan, X.; Zheng, Y. Collaborative mechanism and simulation of low-carbon travel for residents in community-built environment based on evolutionary game. *J. Clean. Prod.* **2024**, *443*, 141098. [CrossRef]

3. Doan, Q.C.; Ma, J.; Chen, S.; Zhang, X. Nonlinear and threshold effects of the built environment, road vehicles and air pollution on urban vitality. *Landsc. Urban Plan.* **2025**, *253*, 105204. [CrossRef]
4. Yang, Y.; Takase, T. Spatial characteristics of carbon dioxide emission intensity of urban road traffic and driving factors: Road network and land use. *Sustain. Cities Soc.* **2024**, *113*, 105700. [CrossRef]
5. Namdeo, A.; Tiwary, A.; Dziurla, R. Spatial planning of public charging points using multi-dimensional analysis of early adopters of electric vehicles for a city region. *Technol. Forecast. Soc. Change* **2014**, *89*, 188–200. [CrossRef]
6. Yang, C.; Zhou, H.; Chen, X.; Huang, J. Demand time series prediction of stacked long short-term memory electric vehicle charging stations based on fused attention mechanism. *Energies* **2024**, *17*, 2041. [CrossRef]
7. Zhu, L.; Zhou, R.; Li, X.; Zhang, L. An evolutionary game analysis of shared private charging pile behavior in low-carbon urban traffic. *Sustainability* **2023**, *15*, 10149. [CrossRef]
8. Karmaker, A.K.; Behrens, S.; Hossain, M.J.; Pota, H. Multi-stakeholder perspectives for transport electrification: A review on placement and scheduling of electric vehicle charging infrastructure. *J. Clean. Prod.* **2023**, *427*, 139145. [CrossRef]
9. Kang, J.; Kong, H.; Lin, Z.; Dang, A. Mapping the dynamics of electric vehicle charging demand within Beijing's spatial structure. *Sustain. Cities Soc.* **2022**, *76*, 103507. [CrossRef]
10. Kuang, H.; Deng, K.; You, L.; Li, J. Citywide electric vehicle charging demand prediction approach considering urban region and dynamic influences. *Energy* **2025**, *320*, 135170. [CrossRef]
11. Zheng, Y.; Keith, D.R.; Wang, S.; Diao, M.; Zhao, J. Effects of electric vehicle charging stations on the economic vitality of local businesses. *Nat. Commun.* **2024**, *15*, 7437. [CrossRef] [PubMed]
12. Li, X.; Li, Y.; Jia, T.; Zhou, L.; Hijazi, I.H. The six dimensions of built environment on urban vitality: Fusion evidence from multi-source data. *Cities* **2022**, *121*, 103482. [CrossRef]
13. Batty, M. Reilly's challenge: New laws of retail gravitation which define systems of central places. *Environ. Plan. A* **1978**, *10*, 185–219.
14. Singh, P.; Khoshaim, L.; Nuwisser, B.; Alhassan, I. How information technology (it) is shaping consumer behavior in the digital age: A systematic review and future research directions. *Sustainability* **2024**, *16*, 1556. [CrossRef]
15. Dinu, O.; Rosca, E.; Burciu, S.; Oprea, C.; Ilie, A.; Stere, A.S.; Rusca, F. Integrative framework for platform-based business models to drive climate neutrality in logistics. *Sustainability* **2024**, *16*, 1418. [CrossRef]
16. Wang, M.; Liang, Z.; Li, Z. Examining spatial disparities in electric vehicle public charging infrastructure distribution using a multidimensional framework in Nanjing, China. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 296. [CrossRef]
17. Zhang, Y.; Tu, T.; Long, Y. Inferring ghost cities on the globe in newly developed urban areas based on urban vitality with multi-source data. *Habitat Int.* **2025**, *158*, 103350. [CrossRef]
18. Yang, X.; Guo, X.; Li, Y.; Yang, K. The sequential construction research of regional public electric vehicle charging facilities based on data-driven analysis—Empirical analysis of Shanxi Province. *J. Clean. Prod.* **2022**, *380*, 134948.
19. Zhang, X.; Du, L.; Song, X. Identification of urban renewal potential areas and analysis of influential factors from the perspective of vitality enhancement: A case study of Harbin city's core area. *Land* **2024**, *13*, 1934. [CrossRef]
20. Sheng, J.; He, Y.; Lu, T.; Wang, F.; Huang, Y.; Leng, B.; Zhang, X.; Chen, Y. Unveiling urban vitality and its interactions in mountainous cities: A human behaviour perspective on community-level dynamics. *Cities* **2025**, *159*, 105780. [CrossRef]
21. Xu, Z.; Chang, J.; Cheng, F.; Liu, X.; Yao, T.; Hu, K.; Sun, J. Examining the impact of the built environment on multidimensional urban vitality: Using milk tea shops and coffee shops as new indicators of urban vitality. *Buildings* **2024**, *14*, 3517. [CrossRef]
22. Tian, X.; He, R.; Sun, X.; Cai, Y.; Xu, Y. An ANFIS-based ECMS for energy optimization of parallel hybrid electric bus. *IEEE Trans. Veh. Technol.* **2019**, *69*, 1473–1483. [CrossRef]
23. Tian, X.; Cai, Y.; Sun, X.; Zhu, Z. Collaborative optimization of fuel economy and battery life for plug-in hybrid electric buses considering traffic condition. *J. Energy Storage* **2024**, *90*, 111928. [CrossRef]
24. Liu, K.; Zhou, D.; Qi, Y.; Zhang, M.; Ren, Y.; Wei, Y.; Wang, J. Exploring the complex effects and their spatial associations of the built environment on the vitality of community life circles using an extreme gradient boosting–shapley additive explanations approach: A case study of Xi'an. *Buildings* **2025**, *15*, 1372. [CrossRef]
25. Li, G.; Luo, T.; Song, Y. Spatial equity analysis of urban public services for electric vehicle charging—Implications of Chinese cities. *Sustain. Cities Soc.* **2022**, *76*, 103519. [CrossRef]
26. Ren, Q.; Sun, M. Predicting the spatial demand for public charging stations for EVs using multi-source big data: An example from jinan city, china. *Sci. Rep.* **2025**, *15*, 6991. [CrossRef]
27. Wang, Z.; Yang, Q.; Wang, C.; Wang, L. Spatial layout analysis and evaluation of electric vehicle charging infrastructure in chongqing. *Land* **2023**, *12*, 868. [CrossRef]
28. Jin, M.-Y.; Zhang, L.-Y.; Peng, Z.-R.; He, H.-D.; Kumar, P.; Gallagher, J. The impact of dynamic traffic and wind conditions on green infrastructure performance to improve local air quality. *Sci. Total Environ.* **2024**, *917*, 170211. [CrossRef]
29. Mao, Y.; Yu, X.; Wang, F.; Zhu, J. Electric vehicle charging demand forecasting: A data-driven integrated learning approach. *Renew. Energy* **2025**, 124141. [CrossRef]

30. Esmaili, A.; Oshanreh, M.M.; Naderian, S.; MacKenzie, D.; Chen, C. Assessing the spatial distributions of public electric vehicle charging stations with emphasis on equity considerations in King County, Washington. *Sustain. Cities Soc.* **2024**, *107*, 105409. [CrossRef]
31. Hou, Y.; Wang, P.; Yao, Z.; Zheng, X.; Chen, Z. Enhancing Electric Vehicle Charging Infrastructure Planning with Pre-Trained Language Models and Spatial Analysis: Insights from Beijing User Reviews. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 325.
32. Chen, P.; Yang, X.; Hao, F.; Tao, R. Decoding electric vehicle adoption using XGBoost and SHAP analysis. *Travel Behav. Soc.* **2026**, *42*, 101125. [CrossRef]
33. Gañan-Cardenas, E.; Rios-Echeverri, D.C.; Ballesteros, J.R.; Branch-Bedoya, J.W. Estimating traffic congestion cost uncertainty using a bootstrap scheme. *Transp. Res. Part Transp. Environ.* **2024**, *136*, 104462. [CrossRef]
34. Zhang, J.; Li, D.; Wang, Y. Toward intelligent construction: Prediction of mechanical properties of manufactured-sand concrete using tree-based models. *J. Clean. Prod.* **2020**, *258*, 120665. [CrossRef]
35. Lundberg, S.M.; Lee, S.-I. A unified approach to interpreting model predictions. *Adv. Neural Inf. Process. Syst.* **2017**, *30*, 4765–4774.
36. Li, J.; Lin, S.; Kong, N.; Ke, Y.; Zeng, J.; Chen, J. Nonlinear and Synergistic Effects of Built Environment Indicators on Street Vitality: A Case Study of Humid and Hot Urban Cities. *Sustainability* **2024**, *16*, 1731. [CrossRef]
37. Zhang, Y.; Wang, X.; Ye, Y.; Wang, L.; Zhang, Y.; Qin, W.; Chi, Y.; Liu, G.; Yao, S. Nonlinear relationships and interaction effects of urban built environment on urban vitality based on explainable machine learning. *City Environ. Interact.* **2025**, *28*, 100244. [CrossRef]
38. Liu, W.; Yang, Z.; Gui, C.; Li, G.; Xu, H. Investigating the Nonlinear Relationship Between the Built Environment and Urban Vitality Based on Multi-Source Data and Interpretable Machine Learning. *Buildings* **2025**, *15*, 1414. [CrossRef]
39. Fan, P.; Bu, S.; Wu, F.; Li, S.; Wen, Y.; Yang, J. Interaction Mechanism Analysis of Rainstorm-Induced Disruptive Incidents in Power and Transportation Systems. *IEEE Trans. Smart Grid* **2026**, *17*, 1–18. [CrossRef]
40. Kang, J.; Kan, C.; Lin, Z. Are Electric Vehicles Reshaping the City? An Investigation of the Clustering of Electric Vehicle Owners' Dwellings and Their Interaction with Urban Spaces. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 320. [CrossRef]
41. Fan, P.; Li, S.; Bu, S.; Wen, Y.; Chung, C.Y. Resilient Power Systems against Wildfire Risks: Towards a Human-Centric and Secure Future. *CSEE J. Power Energy Syst.* **2025**, *11*, 2553–2575.

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