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Exploring the innovation potential of urban space at the micro scale: a case study of Suzhou's main urban area

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As urban areas serve as spatial carriers for innovation activities, exploring the interaction between innovation and urban spaces has become a research hotspot. Previous studies have primarily focused on urban innovation capacity assessment and measurement, with less attention given to the urban innovation potential and issues such as insufficient granularity of research and weak stability in factor weighting. In this study, an urban spatial innovation potential measurement system was proposed from a demand-side perspective, the structural equation model (SEM) was employed to investigate the direct and indirect influences of factors, and micro-scale empirical analysis was conducted in the main urban area of Suzhou, China. Coupling and coordination with innovation outputs were analyzed. The results revealed that (1) the innovation potential exhibits significant spatial clustering characteristics; (2) there is clear core-periphery spatial differentiation in the innovation potential, demonstrating decreasing spatial diffusion effects with distance from the center; and (3) only 8.18% of the plots in the study area occur at the harmonized innovation coupling stage, indicating that the overall innovation conversion efficiency should be improved. This study aimed to provide a sound basis and practical references for optimizing the layout and improving the quality of urban innovation spaces from a detailed scale perspective, thereby enhancing urban competitiveness.

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Introduction

Amid the rise of the knowledge economy and global economic integration, innovation has emerged as a pivotal driver of national economic growth. Cities, which are recognized as incubators and agglomerations for innovation (Gladevich, 2022), channel the synergistic effects of agglomeration and selection (Li et al. 2024) and neighborhood and network dynamics (Venegas and Prudent, 2021) to attract innovative talent and industries, thereby catalyzing innovation activities (Wang et al. 2020). Furthermore, the geographic clustering that characterizes innovation networks promotes knowledge spillovers, significantly enhancing interactions and communication among proximate innovative enterprises, thus expediting the innovation process (Wen et al. 2023; Zhong and Li, 2024). Consequently, the spatial dimension constitutes an integral aspect of urban innovation research. Given the critical role of innovation in today's economic landscape, cities are encouraged to focus on identifying and developing potential innovation spaces to foster the innovation economy and promote sustainable urban development (Li, 2023).

The concept of "innovation potential" differs from "innovation capability," as it not only emphasizes the utilization of existing resources within innovation spaces but also focuses on the potential for dynamic innovation changes in urban areas in future development (MacPherson, 1997; Chehabeddine et al. 2023). In contrast, innovation capability reflects a region's existing achievements, including its realized innovation resources and outcomes, and primarily assesses the immediate performance of innovation in the area. Regions with high innovation potential can rapidly adapt to changes in the market and economic environments, driving economic diversification and enhancing the resilience and adaptability of cities (Caragliu et al. 2009). Furthermore, these regions contribute to urban development by creating environments that attract global talent and investment, making them critical to enhancing urban competitiveness (MacPherson, 1997). Additionally, the interactions and spillover effects of regional innovation hub cities on adjacent cities are crucial (Yang et al. 2024). Gladevich (2022) noted that an accurate assessment of the current situation is the premise of systematic planning. To improve the efficiency of urban innovation resource utilization, clear guidance for innovative spatial layout planning is necessary. Assessing the innovation potential of urban spaces can not only clarify the suitability of different regions for conducting innovation activities but also guide the development of spatial functions, thus promoting the establishment of an organic and diversified urban spatial system that supports various innovation activities (Duan et al. 2024). Therefore, this paper focuses on measuring the urban innovation potential to foster long-term development and the establishment of sustainable innovation ecosystems.

Existing studies have shown that innovation activities significantly depend on space (Krugman, 1991; Feldman and Florida, 1994), suggesting that different regions exhibit varying abilities to support innovation (Porter, 1998; Bathelt et al. 2004). The formation of urban innovation space is a complex and multifactorial process (Evans, 2009). A comprehensive understanding of the spatial differences in innovation activities and the driving forces underlying them is crucial for revealing the formation mechanisms of urban innovation potential. Some studies have focused on exploring the production side of the urban innovation space, specifically, the relationships among innovation production, R&D investment, enterprise efficiency, and the spatial distribution of cities (Audretsch and Feldman, 1996; Zucker et al. 1998). However, this perspective often overlooks the 'demand side' of innovation potential development, which includes micro-level driving factors behind innovation activities,

such as the needs of innovative enterprises, the demands of innovative talent, and the environments that support social interaction and creative exchange (Glaeser and Gottlieb, 2006; Boschma, 2005). Consequently, the examination of urban innovation potential must encompass not only industrial and economic facets but also social and environmental dimensions. Additionally, the efficiency of innovation conversion in urban spaces must be considered; a high conversion efficiency indicates that a given city can effectively transform its innovation potential into actual innovation performance (Ma et al. 2023). Nevertheless, in the practical development of urban areas, the question of whether the innovation potential of land parcels is being efficiently converted into innovation capability remains underexplored. By conducting a detailed analysis of the coordinated development between urban innovation potential and outputs, this study aims to uncover the efficiency and alignment of urban innovation resource allocation.

Overall, despite studies discussing the spatial characteristics of innovation activities (Feldman and Florida, 1994; Lim, 2003), there is a lack of interest in potential measurement (Chen et al. 2022b), a tendency towards overly broad research scales (Lu et al. 2022), weak stability in factor weighting (Qiu et al. 2020; Wang and Liu, 2020), and insufficient exploration of the match between innovation potential and outputs (Nasir et al. 2022). Given these research gaps, this study aims to answer the following questions:

At the micro-scale, what are the key factors influencing the innovation potential of urban spaces?

How are urban innovation potential and outputs coordinated, and how can we identify and address areas of misalignment?

To address the identified issues, this study is grounded in a micro-perspective, focusing on measuring innovation potential at the micro-plot scale. Starting from the demand side, this study delves into the fundamental drivers of innovation potential and examines the specific environment, distribution of enterprises and talent, and their interactions within the unit to gain a more nuanced understanding of urban innovation potential. Specifically, this paper employs a structural equation model (SEM) as the principal quantitative research tool. The SEM enables a detailed evaluation of the diverse factors impacting innovation potential, effectively managing complex intervariable relationships, and elucidating both direct and indirect pathways of influence. Additionally, this paper uses a coupling coordination degree model (CCDM) to assess the coordination level between innovation potential and outputs, identifying critical innovation nodes and potential clusters, and highlighting areas where coordination is lacking. This research aims to provide targeted recommendations for specific parcels, aiding policymakers in optimizing innovation resource allocation and developing long-term urban planning and development strategies.

Literature review

Research on the spatial distribution of innovative activities.

Economist Joseph Schumpeter first introduced the concept of innovation in 1934, which laid the foundation for the development of related theories such as the growth pole (Perroux, 1963), agglomeration economies (Button, 1976), and the product life cycle (Vernon, 1966). These theories collectively focus on the relationship between enterprise innovation and regional economics, highlighting the dependence of innovation on geographical space. Existing quantitative research primarily focuses on measuring the geographical distribution of innovation (Feldman and Florida, 1994; Lim, 2003), the spillover effects of innovation space, and innovation network connections (Inkinen and Kaakinen, 2016; Li et al. 2023).

In contemporary discourse, investigations into innovation with respect to urban spatial development have primarily focused on the manifestation of innovation capabilities within urban spaces and the distribution characteristics of innovation spaces. A relative scarcity of research measures the innovation potential of urban spaces, with the majority concentrating on assessing innovation capacity. Lim (2003) analyzed and evaluated the spatial distribution differences in innovation activities among U.S. metropolitan areas and reported significant correlations between the concentration of innovation activities in metropolitan areas and neighboring regions. This phenomenon has also been observed in Quebec Province, Canada (Shearmur and Doloreux, 2009), and the Helsinki Metropolitan Area, Finland (Inkinen and Kaakinen, 2016). Research on China mainly focuses on the country (Li et al. 2015), metropolitan areas, provinces, and cities as study units, such as the Pearl River Delta (Lin et al. 2019; Wu et al. 2021), the Greater Bay Area (Qiu et al. 2020; Chen et al. 2022b), Zhejiang Province (Jiang, 2014; Zhu et al. 2023), and other regions with high innovation capacity. In a study of three case cities Beijing, Shenzhen, and Shanghai, Chen et al. (2022a) analyzed urban innovation spatial patterns and associated characteristics, thereby summarizing regional organizational models of urban innovation spaces. Most studies adopt a macro-spatial perspective, employing the entire city as the unit of spatial analysis (Lu et al. 2022), which impedes a detailed interpretation of innovation activities at smaller scales.

Simultaneously, it is important to recognize that the genesis and evolution of urban innovation spaces are intricately intertwined with the innovative endeavors undertaken within them (Li and Liu, 2018). A nuanced examination of the spatial differences in these innovative activities and their underlying determinants is vital.

Meijer and Thaens (2016) identified the primary participants in urban technological innovation activities as technology enterprises, local governments, research institutions, and the surrounding citizenry. From an enterprise cluster development perspective, human resources and financial investment, R&D allocation, organizational culture, and innovation management are considered the main constraints on innovation spatial development (Babkin et al. 2015). Subsequently, Li et al. (2016) proposed that innovation is mainly influenced by core elements, technological infrastructure, the innovation environment, and supporting conditions. After determining the weight of each indicator using the analytic hierarchy process (AHP), a comprehensive overlay was applied to derive the urban innovation potential. Qiu et al. (2020) developed a comprehensive spatial indicator system leveraging point of interest (POI) data to assess the science and technology innovation potential, focusing on knowledge innovation, technological innovation, and the innovation environment. They employed the AHP to obtain indicator weights, enabling detailed analysis of innovation potential concentration and diversification in the Guangdong-Hong Kong-Macao Greater Bay Area. Both Wang and Liu (2020) and Lu et al. (2022) developed multidimensional assessment frameworks for evaluating the impact of technological innovation potential considering innovation resources and environments. They utilized the Delphi method to calculate factor weights and conducted multifactor weighted spatial composite evaluations.

In addition to innovation activities within enterprises (Evans, 2009; Hutton, 2006), innovation platforms (Zukin, 2021), the urban built environment (Mariotti et al. 2023; McNeill, 2021), institutional tools (Li and Wang, 2019; Luo and Chan, 2020), and social interactions (Wijngaarden et al. 2020; Zhu et al. 2023) contribute to the emergence and development of urban innovation spaces. This perspective aligns with the multidimensional framework proposed by Adu-McVie et al. (2021). Moreover, the

role of regional innovation hub cities should not be overlooked. These cities significantly influence surrounding cities through various mechanisms, such as knowledge spillovers, industrial chain expansion, and policy innovation. By facilitating interactions and generating spillover effects, they drive technological innovation and promote economic integration in the region (Cooke et al. 1997; Morgan, 2004; Bathelt et al. 2004). Therefore, a comprehensive consideration of these factors can facilitate a more holistic understanding of the formation and evolution of urban innovation spaces. Additionally, in these studies, subjective weighting methods were often employed to determine weights, which could yield unstable weight values and fail to reflect the complex interactions among multiple indicators (Buchecker and Frick, 2020). Thus, overcoming the homogenization issue of factor weighting methods is crucial.

Relationship between the innovation potential and innovation outputs.

In the field of innovation management, the relationship between innovation potential and innovation outputs is key to assessing the efficiency of a given urban or regional innovation system (Crescenzi et al. 2016). Innovation potential refers to the various latent resources and conditions within an area that facilitate innovation activities, describing the capability for future innovation activities (Chehabeddine et al. 2023). Innovation outputs, such as the number of patents, the volume of scientific papers published, or the number of new products launched, directly represent the results of innovation activities (Hall et al. 2005; Griliches, 1990). Understanding the relationship between these two factors not only helps in evaluating the alignment of the existing innovation environment and the effectiveness of innovation policies but also helps guide future urban spatial planning more precisely to better facilitate innovation activities (Li et al. 2019).

The interaction between innovation potential and innovation output is a complex process involving multiple factors (Jiang, 2014; Liu et al. 2020). Jaffe (1989) reported that through effective knowledge management and technology transfer, innovation potential could facilitate an increase in innovation outputs. Additionally, Furman et al. (2002) emphasized that the national innovation system (e.g., policy support and the market environment) is crucial for transforming innovation potential into outputs. The motivation for cities to engage in collaborative innovation efforts can be regarded as the realization of patent value, effective improvement in academic standards, and the development and production of new products (Lee, 1996). Jurowetzi et al. (2018) applied the case study method to analyze the effects of cooperation and competition relationships among firms within industrial clusters on the utilization of innovation potential and the realization of innovation outputs. However, current research on the relationship between innovation potential and outputs often focuses on economic and management perspectives, with less attention paid to the spatial dimension of their alignment and coordination (Zhang et al. 2020; Qamruzzaman, 2021; Wang et al. 2022). This limitation leads to an insufficient understanding of how innovation activities in various spaces affect the realization of innovation potential.

Additionally, regarding the quantification of innovation output indicators, we believe that although patent data represent only a portion of innovation outputs, their accessibility, quantifiability, and specificity make them reliable indicators for assessing technological innovation and innovative capacity (Carlsson et al. 2002). Patent information not only provides detailed insights into technological advancements but also reflects the level of innovation activity and technological development capability within a region (Archibugi and Pianta, 1996). Acs

Table 1 Data sources.

Category	Names	Data source	Year	Source URL
Innovation platforms	Unicorn incubator enterprises; gazelle enterprises; high-tech enterprises; innovation parks; banks; financial institutions Co-creation spaces; incubators	Suzhou Science and Technology Finance Ecological Circle Service Platform Suzhou Double Innovation Center	2022	http://kjlr.kj.suzhou.com.cn/
Built environment	Provincial-level or above enterprise R&D centers; major innovation platforms; colleges and universities; scientific research institutions Parks and green spaces; subway stations; bus stations; leisure and entertainment facilities; dining facilities; sports facilities; primary and secondary schools; hospital facilities Main rivers; major roads; city administrative boundaries	Suzhou Open Innovation Cooperation Heatmap Gaode Map	2022	http://www.szscdyz.com/szscpsenvplat/esp/apps/espp/ http://rit.suzhou.gov.cn/rit20/TZSZMap/index.html/ https://lbs.amap.com/
Population activity	Distribution of the population with a college education or higher Nighttime light intensity	Open Street Map (OSM) World Pop Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences	2022 2020 2021	https://www.openstreetmap.org/ https://wopr.worldpop.org/ http://www.resdc.cn/

et al. (2002) found that regions and firms with a higher number of patents often demonstrate stronger economic growth and higher innovation efficiency, indicating that patents can serve as a credible signal of technological innovation. Feldman and Florida (1994) emphasized a significant positive correlation between the level of patent development and the concentration of innovation activities. These studies indicate that patent data can serve as an important metric for measuring regional innovation capacity (Roper and Hewitt-Dundas, 2015; Donoso, 2017).

To deepen the understanding of the interaction between innovation potential and innovation output, this study introduces the CCDM, an effective tool for assessing the interdependence and collaborative relationships between these elements (Ponta et al. 2021; Geng et al. 2022). This model has been widely used in related research. For instance, Gu (2023) used the CCDM to measure the integration level of industrial chains and innovation chains across 30 provinces in mainland China, investigating its impact on the efficiency of innovation resource utilization. Liu and Li (2024) applied the CCDM to analyze the coupling coordination between high-quality urban development and technological innovation systems, revealing the advantages of knowledge creation and technology acquisition in China’s eastern coastal regions. Similarly, Cheng et al. (2023) analyzed the coupling coordination between innovation networks and eco-efficiency, extending the application of the model to environmental efficiency. In the CCDM, the concept of “coupling” refers to the interaction and influence between two or more systems (Geng et al. 2022). This interaction can be positive, promoting synergistic development between systems, or negative, leading to conflicts and discoordination. “Coordination,” on the other hand, is based on the interrelationship of systems, emphasizing the importance of positive interactions between subsystems for overall system development (Pan et al. 2021; Gao et al. 2023). These studies indicate that the CCDM can analyze interactions and effects between two or more systems, helping to reveal the dynamics within the innovation system, identify areas of misalignment between innovation potential and output (He et al. 2024), and provide a scientific basis for formulating effective innovation policies and optimizing resource allocation (Sun et al. 2023).

Study area and data

Study area. This paper selects the main urban area of Suzhou as a case study due to its transformation from a historic cultural city in China to a modern, innovative city. Compared with other advanced cities, Suzhou, which is an emerging hub of innovative development, merits in-depth study for its sustained innovation potential. The study area includes five districts, namely, Gusu District, High-Tech District, Wuzhong District, Xiangcheng District, and Industrial Park District, which cover a total land area of ~1754 square kilometers. The urban road network was used as the boundary for the urban regional division, dividing the network into 1051 land plot units (Fig. 1).

Data

Data sources. The empirical analysis in this study is underpinned by a tripartite data framework comprising innovation platform data, built environment data, and population activity data (Table 1). The innovation platform data were collected through an application programming interface (API) bulk scraping, encompassing 12 types of related facility points. The built environment data include open street map (OSM) vector data and POI data, covering information such as names, categories, and coordinates. The population activity data are divided into population distribution data and nighttime light brightness data.

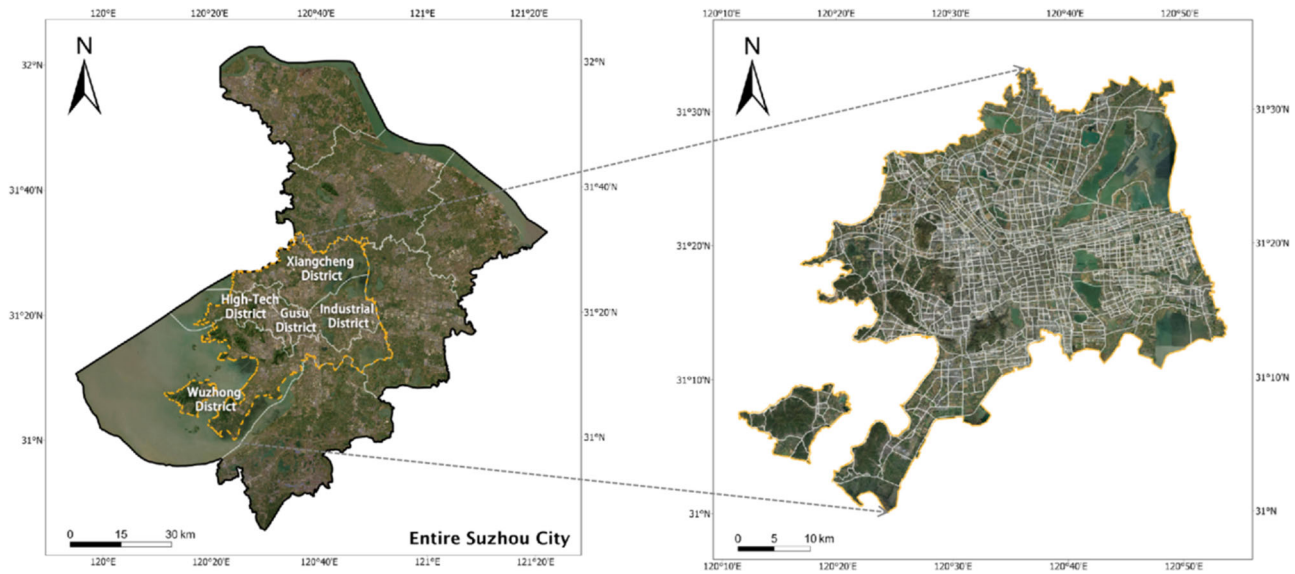


Fig. 1 Study area. The map showing the five study districts (Gusu, High-Tech, Wuzhong, Xiangcheng, Industrial Park) divided into 1051 land plot units.

Data processing. To construct an initial indicator framework aimed at quantifying the urban spatial innovation potential, it is essential to quantify each constituent indicator, which can be categorized into three types: density, distance, and remote sensing indicators.

- (1) Density indicators encompass data related to innovation platforms as well as built environment data on leisure and entertainment facilities, dining facilities, sports facilities, primary and secondary schools, and hospitals. According to the first law of geography and location influence, kernel density analysis is performed on point data with a bandwidth set to 300 meters, which is generally considered to be the size of a neighborhood block (Niu et al. 2023). Kernel density estimation reflects the degree of spatial distribution clustering and the distance decay effect of elements. The average kernel density values of various units are summarized based on the mean values of the land parcels.
- (2) Distance indicators include distances to parks and green spaces, major rivers, metro stations, bus stations, and main roads within the built environment. Network analysis tools are used to calculate distance costs, assigning appropriate travel speeds based on a constructed road network dataset. Interpolation calculations are then performed on the results to obtain distance cost rasters covering the study area, which are then summarized into land parcel units based on the mean values. Additionally, to accurately calculate the distances between each plot and the center of Shanghai, which is the closest innovation center city to the study area, we convert the plot areas and the Shanghai administrative boundary into point features. These points are positioned at the geometric centers of their respective features, allowing us to calculate the corresponding distances effectively.
- (3) Remote sensing indicators include population distribution data and nighttime light brightness data. The corresponding remote sensing data raster units, which are already assigned values, are processed by calculating the average value of all the pixels within the research land parcel area. This average is used as the representative value for the land parcel unit.

Moreover, to mitigate the adverse impacts of dimensional variance among indicators on the analytical model, in this

research, the min-max normalization technique is adopted for indicator standardization. Density and remote sensing indicators are typically subjected to positive normalization, whereas distance indicators are generally subjected to inverse normalization.

Methodology

To comprehensively assess the innovation potential of urban spaces, this study employs the SEM and the CCDM. The SEM is a multivariate statistical technique that examines relationships among multiple variables and quantifies the direct and indirect effects of factors on overall innovation potential. This provides a reliable framework for evaluating innovation potential. The CCDM analyzes the coordination between innovation potential and innovation output, identifying efficient and disorganized areas within the innovation system. This helps optimize innovation resource allocation and improve system coordination.

Building an innovation potential measurement model based on the SEM

Constructing an indicator system. Grounded in an extensive review of the extant literature on the determinants of the spatial distribution of innovation activities, this paper starts from the micro-level “demand side” of urban spatial innovation. It decomposes the elements of the demand layer and categorizes multiple influences such as resources, talent, environment, and society. We propose an explanatory framework that comprises three dimensions: innovation-driving forces, innovation resource support, and innovation environment quality (Fig. 2).

Innovation driving forces catalyze the allocation and employment of resources for innovation (Hutton, 2006), whereas innovation resource support facilitates the establishment of platforms for the transmutation of innovative outcomes (Sun et al. 2020). Simultaneously, the quality of the innovation environment determines the occurrence of favorable external conditions (Hamidi and Zandiatahbar, 2019). These three dimensions interact with each other to collectively enhance the potential for urban spatial innovation, thus driving the cyclical generation and development of the urban spatial innovation system.

The development of an urban spatial innovation potential measurement index system involves the following steps:

- Step 1: Selection and Grouping of the Indicators

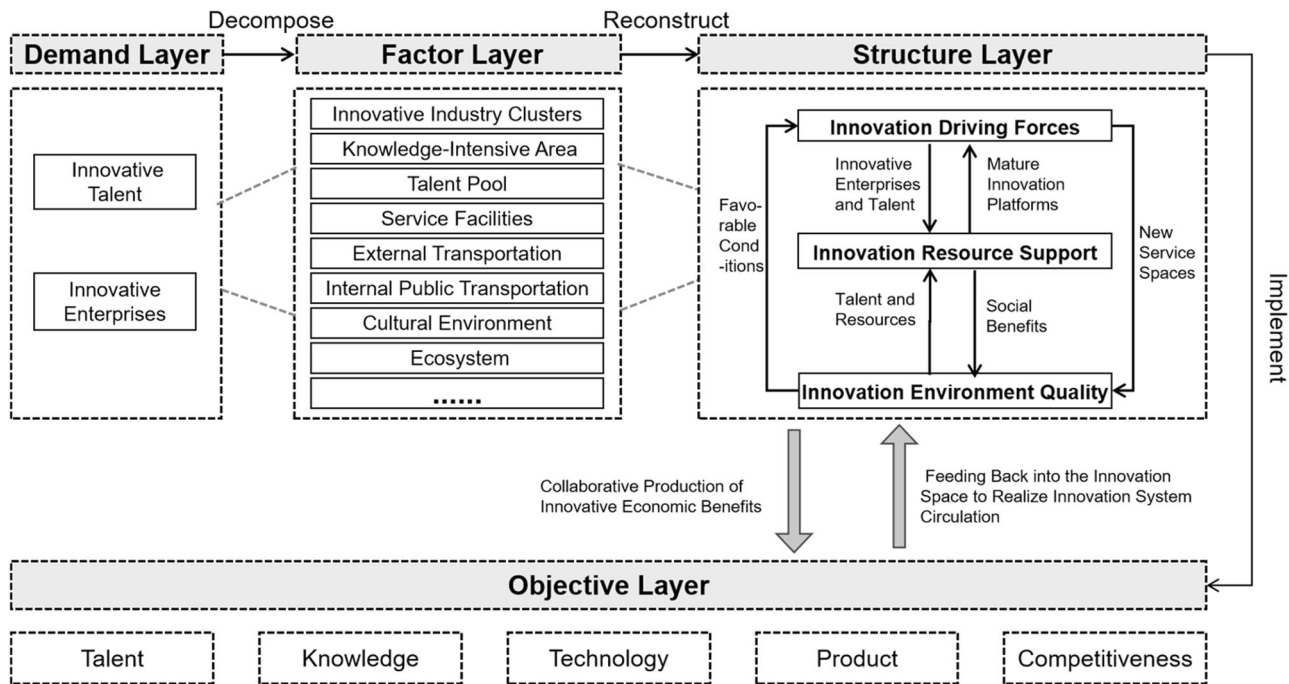


Fig. 2 Framework construction approach. The figure illustrates the three-dimensional structure of innovation potential, comprising innovation-driving forces, innovation resource support, and innovation environment quality, and elucidates their interrelationships.

Table 2 Urban spatial innovation potential measurement index system.

Latent variable	Item	Observed variable	Item
Urban spatial innovation potential η	Innovation driving forces ξ_1	Gazelle enterprise density	X_1
		High-tech enterprise density	X_2
		College and Research Institute density	X_3
		Scientific research institution density	X_4
		Population with a college education or higher distribution	X_5
		Straight-line distance from the Center of Shanghai	X_6
	Innovation resource support ξ_2	Co-working space density	X_7
		Incubator density	X_8
		Startup park density	X_9
		Venture capital institution density	X_{10}
		Bank density	X_{11}
		Provincial-level and above enterprise R&D center density	X_{12}
	Innovation environment quality ξ_3	Major innovation platform density	X_{13}
		Distance to parks and green spaces	X_{14}
		Distance to major rivers	X_{15}
		Distance to subway stations	X_{16}
		Distance to bus stations	X_{17}
		Distance to main roads	X_{18}
		Dining facility density	X_{19}
		Sports facility density	X_{20}
		Primary and secondary school density	X_{21}
		Hospital facility density	X_{22}
Nighttime light intensity	X_{23}		

Based on the previously defined dimensions, we selected and grouped indicators to establish a three-level urban spatial innovation index system comprising 25 observable indicators.

Step 2: Indicator Clustering via Pearson Correlation and the Furthest Neighbor Method

The indicators were clustered using the furthest neighbor method based on Pearson correlation. The categories in the clustering tree containing a single indicator were directly incorporated into the final index system. Regarding categories with two or more indicators, a significance test for differences was

conducted. For categories with exactly two indicators, the Wald-Wolfowitz runs test was applied. Regarding categories encompassing more than two indicators, Kruskal-Wallis one-way analysis of variance by ranks was used.

Step 3: Classification and Further Analysis of the Indicators within the Same Cluster

Indicators within the same cluster were classified based on the presence of significant differences. If significant differences existed between indicators, those in categories with exactly two indicators were directly included in the final system. For

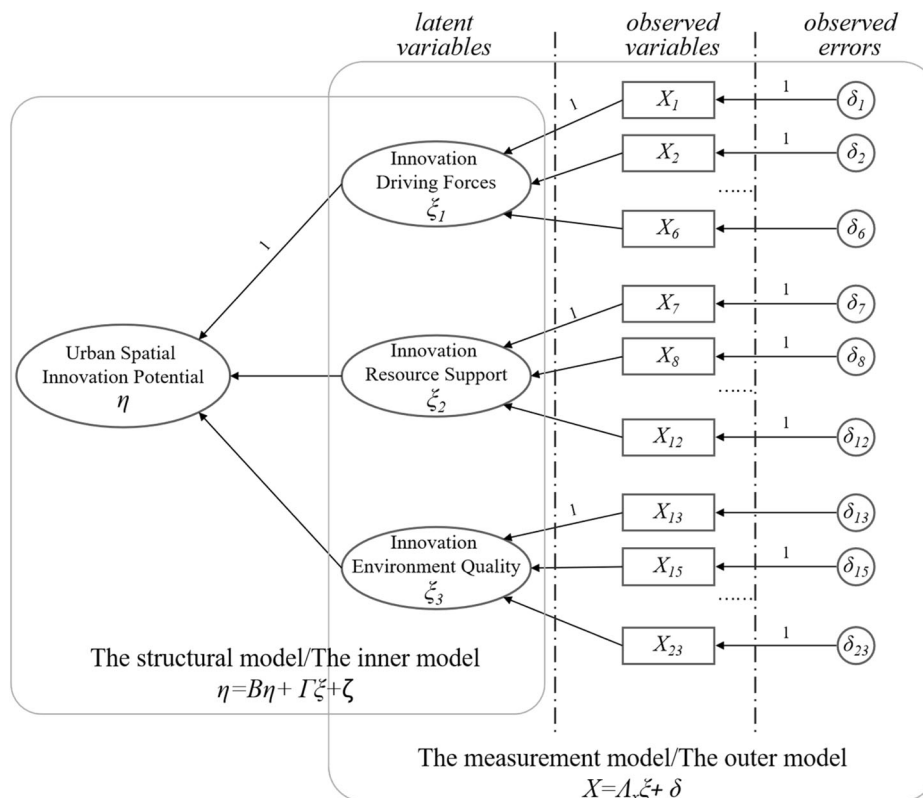


Fig. 3 Initial structural equation model. The initial SEM framework incorporating four latent variables and 23 observed variables, capturing 26 path relationships to elucidate the urban spatial innovation potential.

categories with more than two indicators, empirical judgment was used to eliminate specific indicators before further clustering analysis. This process was continued until no significant differences remained between indicators within the same category.

Following the established procedure and eliminating significantly correlated indicators, the density of unicorn incubator enterprises and the density of leisure and entertainment facilities were removed. Consequently, of the 25 initial indicators, 23 observable indicators were selected and defined as observed variables in the exogenous latent variable model Table 2.

Model assumptions, verification, and modification. The SEM paradigm combines factor and path analysis methodologies, providing an effective framework for elucidating the complex interrelations among numerous variables. Through detailed selection and refinement of the observable variables, this approach aims to analyze the influences of three latent variables—innovation driving forces, innovation resource support, and innovation environment quality—on urban spatial innovation potential. The proposed hypotheses are as follows:

Hypothesis H1: The latent variable innovation driving forces are positively correlated with the enhancement of urban spatial innovation potential.

Hypothesis H2: The latent variable innovation resource support is positively correlated with the enhancement of urban spatial innovation potential.

Hypothesis H3: The latent variable innovation environment quality is positively correlated with the enhancement of urban spatial innovation potential.

Consistent with the hypotheses above, the established SEM framework for revealing the urban spatial innovation potential

incorporates four latent variables and 23 observed variables and captures 26 path relationships (Fig. 3).

For all the measurement indicators, the Kaiser-Meyer-Olkin (KMO) test and Bartlett’s sphericity test were conducted. The KMO value was 0.862, indicating notable intercorrelations among the measurement indicators and suggesting that the indicators are suitable for measuring the latent variables. The results of Bartlett’s sphericity test revealed that the data did not support the assumption of a spherical covariance matrix, which suggests that the data are suitable for factor analysis.

The measurement indicators were subjected to a multivariate normal distribution test, where the overall p value was 0.0, indicating significant deviations from the requirements of a normal distribution in terms of skewness and kurtosis. The characteristics of the study data, including large sample size, significant non-normality, and high model complexity, conform with the prerequisites for employing the asymptotic distribution free (ADF) technique (Kline, 2018). Hence, the ADF approach was employed for parameter estimation in the subsequent analytical procedures.

After modification, the final model was obtained, as shown in Fig. 4, with the fit parameters detailed in Table 3. Despite the less-than-ideal chi-square to degrees of freedom ratio value, which may be related to fitting challenges associated with the large sample size, other indices, such as the goodness-of-fit index, root mean square error of approximation, normed fit index, and comparative fit index, satisfied the model adaptation criteria. This finding indicates that optimal model parameter estimation was achieved.

The model computations confirmed the hypotheses, as detailed in Table 4, highlighting the successful implementation of the confirmatory factor analysis (CFA) process.

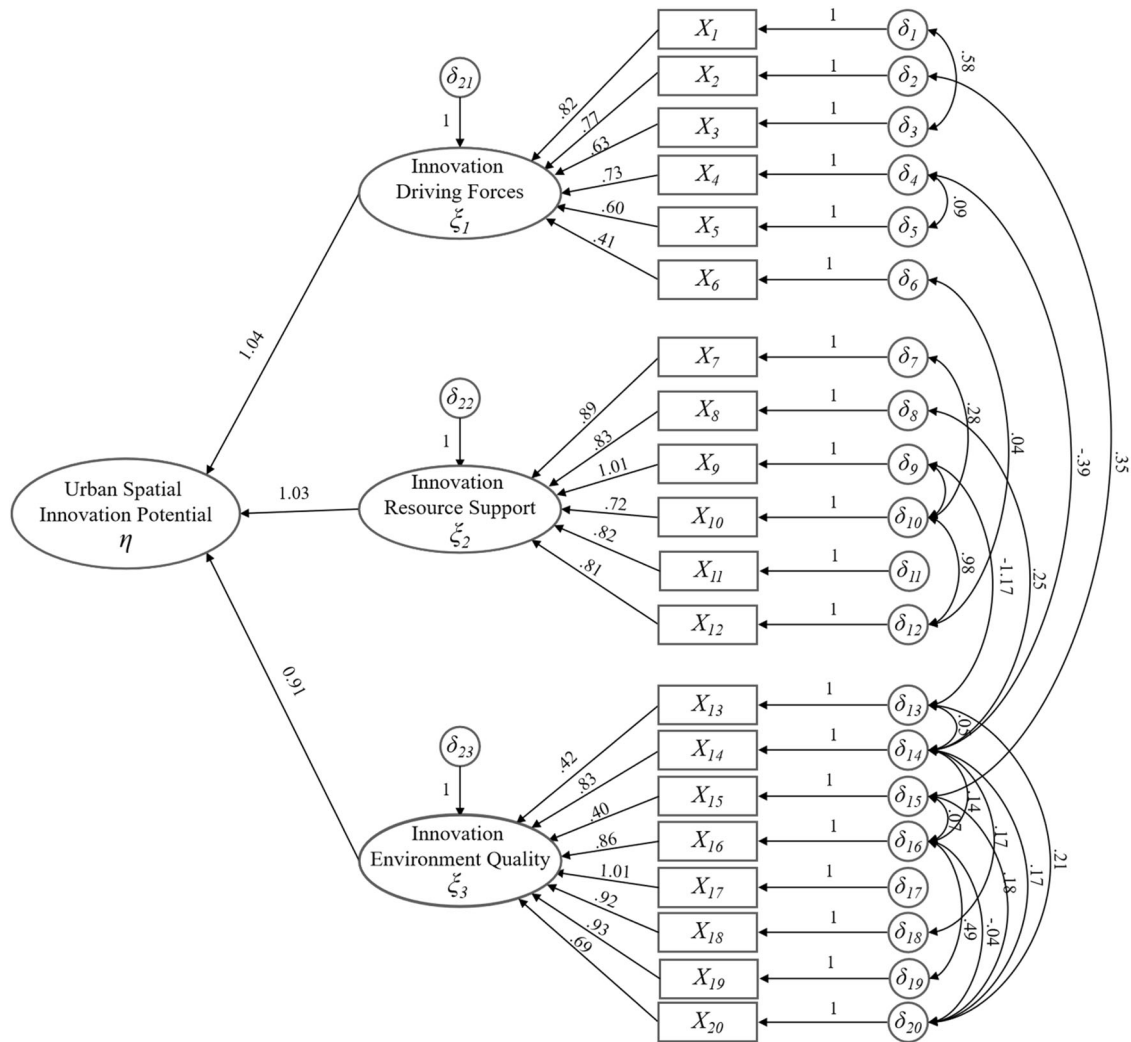


Fig. 4 Revised structural equation model. The final model incorporating four latent variables and 20 observed indicators, adjusted through a series of statistical tests and estimated using the ADF approach.

Table 3 Final computed fit indices.

Indicator name	Fit criterion	Computed result	Model evaluation	
Absolute fit indices	CMIN/DF	Less than 3	9.036	Poor fit, potentially due to the large sample size
	GFI	Greater than 0.80	0.922	Good fit
	RMSEA	Below 0.05 is excellent; 0.05 to 0.08 is favorable	0.75	Good fit
Relative fit indices	NFI	Greater than 0.80; closer to 1 is better	0.82	Acceptable fit
	CFI	Greater than 0.80; closer to 1 is better	0.86	Acceptable fit

Table 4 Verification of the research hypotheses.

Hypothesis	Estimate	Significance	Validation result
H1: The latent variable innovation driving forces affect urban spatial innovation potential	1.04	Significant	Supported
H2: The latent variable innovation resource support affects urban spatial innovation potential	1.03	Significant	Supported
H3: The latent variable innovation resource support affects urban spatial innovation potential	0.91	Significant	Supported

Table 5 Computed indicator weights.

Endogenous latent variable (η)	Exogenous latent variable (ξ)	Standardized loading coefficient	Item weight	Observed variables	Standardized loading coefficient	Item weight	
Urban spatial innovation potential (η)	Innovation driving forces (ξ_1)	1.04	0.349	Gazelle enterprise density (X_1)	0.82	0.208	
				High-tech enterprise density (X_2)	0.77	0.196	
				College and research institute density (X_3)	0.61	0.155	
				Scientific research institution density (X_4)	0.73	0.185	
				Population with a college education or higher distribution (X_5)	0.60	0.152	
				Straight-line distance from the center of Shanghai (X_6)	0.41	0.104	
				Co-working space density (X_7)	0.89	0.175	
				Incubator density (X_8)	0.83	0.163	
				Startup park density (X_9)	1.01	0.199	
				Venture capital institution density (X_{10})	0.72	0.142	
		Innovation resource support (ξ_2)	1.03	0.346	Bank density (X_{11})	0.82	0.161
				Provincial-level and above Enterprise R&D center density (X_{12})	0.81	0.160	
				Distance to parks and green spaces (X_{13})	0.42	0.069	
				Distance to subway stations (X_{14})	0.85	0.140	
				Distance to bus stations (X_{15})	0.40	0.066	
				Dining facility density (X_{16})	0.86	0.141	
				Sports facility density (X_{17})	1.01	0.166	
				Primary and secondary school density (X_{18})	0.92	0.151	
				Hospital facility density (X_{19})	0.93	0.153	
				Nighttime light intensity (X_{20})	0.69	0.114	
	Innovation environment quality (ξ_3)	0.91	0.305				

Table 6 Statistical description of the elements by region.

Region name	Number of units	Element name	Minimum value	Maximum value	Mean value	Standard deviation	Innovation potential score
High-tech district	142	Innovation driving forces	0.0157	0.2372	0.0971	0.0623	0.1598
		Innovation resource support	0.0000	0.4895	0.0812	0.0824	
		Innovation environment quality	0.2177	0.5563	0.3207	0.0773	
Industrial park district	279	Innovation driving forces	0.0821	0.6339	0.1471	0.0817	0.1968
		Innovation resource support	0.0013	0.5677	0.1261	0.0796	
		Innovation environment quality	0.2429	0.5660	0.3338	0.0625	
Gusu district	119	Innovation driving forces	0.0548	0.2770	0.1133	0.0553	0.2088
		Innovation resource support	0.0002	0.2037	0.0645	0.0498	
		Innovation environment quality	0.2839	0.8254	0.4817	0.0795	
Wuzhong district	298	Innovation driving forces	0.0000	0.1969	0.0718	0.0381	0.1267
		Innovation resource support	0.0000	0.4895	0.0297	0.0679	
		Innovation environment quality	0.1651	0.5976	0.2995	0.0757	
Xiangcheng district	213	Innovation driving forces	0.0278	0.1284	0.0722	0.0175	0.1281
		Innovation resource support	0.0000	0.1772	0.0312	0.0368	
		Innovation environment quality	0.2110	0.4350	0.3021	0.0482	
Suzhou main urban area (total)	1051	Innovation driving forces	0.0000	0.6339	0.1034	0.0662	0.1594
		Innovation resource support	0.0000	0.5476	0.0615	0.0762	
		Innovation environment quality	0.1651	0.8254	0.3344	0.0946	

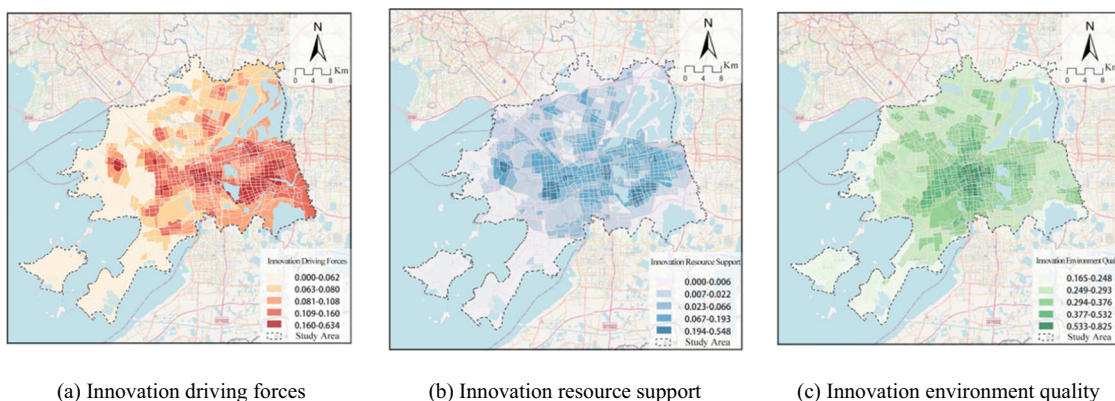


Fig. 5 Spatial distributions of the exogenous latent variables. a Innovation driving forces. **b** Innovation resource support. **c** Innovation environment quality.

Determination of Index Weights. The weights of the indicators were computed to quantify their relative contributions to the overall framework. The calculation involved softmax transformation, a generalization of the logistic function that aims to convert a set of values into probabilities that sum to one.

Let $X = \{X_1, X_2, \dots, X_n\}$ represent a set of values corresponding to either observed indicator loadings or latent variable loadings. To normalize these values within their respective groups, we defined the softmax function $S(X^{(k)})$ for a subset $X^{(k)}$ of X , where k denotes the subset and i_k is the set of indices within that subset.

Each element $x_i^{(k)}$ in subset $X^{(k)}$ can be transformed into a normalized weight $P_i^{(k)}$ as follows:

$$P_i^{(k)} = \frac{e^{x_i^{(k)}}}{\sum_{j \in i_k} e^{x_j^{(k)}}} \tag{1}$$

This transformation ensures that the sum of the normalized weights of each subset $X^{(k)}$ equals one:

$$\sum_{i \in i_k} P_i^{(k)} = 1 \tag{2}$$

Softmax transformation was applied to each of the various subsets: $X^{(1)}$ corresponds to the observed indicators within each latent variable (e.g., $X^{(1)} = \{X_1, \dots, X_5\}$), and $X^{(2)}$ corresponds to the latent variables within the overall framework (e.g., $X^{(2)} = \{\xi_1, \xi_2, \xi_3\}$), thereby normalizing each element within its respective group Table 5.

Coupling coordination degree model. The CCDM is a key tool used in this study to analyze the level of coordinated development between innovation potential and innovation output (Geng et al. 2022). This model evaluates the optimization of innovation resource allocation and the coordination of innovation activities in urban spaces, thereby revealing whether innovation potential and innovation output achieve positive interactions.

In this model, two systems represent innovation potential and innovation outputs. Innovation potential is determined based on the SEM analysis discussed above, while innovation outputs are primarily measured using patent data from the main urban area of Suzhou. The patent data were obtained through web scraping and analyzed for geolocation based on patent addresses. Considering that innovation knowledge spillover effects are more likely to occur on a scale of 1 kilometer (Rosenthal and Strange, 2003), kernel density analysis is performed to obtain the average values of the plots, and the innovation output intensity of the statistical unit plots is calculated. The innovation output intensity

of each land parcel is computed using kernel density analysis followed by averaging over the plots.

The coupling degree (C) and coordination degree (D) between innovation potential and innovation output indicate their basic relationship and the extent of their synergistic development. The coupling degree reflects the strength of their association, whereas the coordination degree assesses the level of synergy. A higher coordination degree means a more ideal mutual promotion relationship between innovation potential and innovation output (Pan et al. 2021).

The coordination degree can be calculated as follows:

$$C = 2 \sqrt{\frac{X \times Y}{(X + Y)^2}} \tag{3}$$

where C denotes the degree of coupling, with values ranging from 0 to 1. Moreover, X and Y denote the systems of the innovation potential and innovation outputs, respectively.

$$D = \sqrt{C \times T} \tag{4}$$

$$T = \alpha(X) + \beta(Y) \tag{5}$$

where D denotes the coordination degree, and T is the comprehensive harmonized index of innovation potential and innovation outputs. The coefficients α and β can be determined. Given that the levels of innovation potential and innovation outputs are considered equivalent, both coefficients are set to 0.5. The coordination degree D ranges from 0 to 1, where a higher value indicates a greater degree of coordination.

Empirical results

Quantitative description of innovation potential indicators. In this investigation, a detailed descriptive statistical analysis of innovation potential is conducted across five urban districts in the main urban area of Suzhou, focusing on three key exogenous latent variables. This analysis can provide insights into the innovation data characteristics of each region (Table 6).

Gusu District presented a cumulative innovation potential index of 0.2088, indicating a promising trajectory for future innovation. The innovation environment in Gusu District is distinguished by its superior quality relative to its counterparts, coupled with a smaller standard deviation. These characteristics denote a greater degree of stability and equilibrium within the innovation ecosystem, providing a robust foundation for innovation. Although this district may not exhibit numerical superiority in terms of innovation drivers and resource support, the premium and sustainable nature of its innovation environment can provide a more substantial base for developing its innovation potential.

Closely following is the Industrial Park District, which achieved a score of 0.1968. Its performance in terms of innovation driving forces and innovation resource support significantly exceeds that of other districts. However, a higher standard deviation suggests an uneven distribution of innovation activities within the district, characterized by a clear divide between leaders and laggards. The High-Tech District, with an innovation potential index of 0.1598, was ranked third, indicating certain advantages in overall innovation capacity but was nevertheless slightly inferior to the Gusu District and Industrial Park District.

In contrast, the Wuzhong District and Xiangcheng District did not reach the median comprehensive innovation potential score, with values of 0.1267 and 0.1598, respectively. The maximum and average values of the indicators were generally lower, indicating a lower level of innovation activity in these areas, while the distribution of innovation resources and the quality of the environment were relatively balanced, lacking outstanding performance overall.

Spatial distribution characteristics of the exogenous latent variables. In this investigation, weighted statistical analysis was employed to comprehensively examine the spatial distribution patterns of the three crucial exogenous latent variables above: innovation driving forces, innovation resource support, and innovation environment quality.

Across all exogenous latent variables, a universal pattern of point clustering and group linkages emerged, with slight variations in distinct spatial attributes. The spatial features of innovation driving forces (Fig. 5a) and innovation resource support (Fig. 5b) largely exhibited multicentric distributions, which were concentrated in the Gusu District, Industrial Park District, and High-Tech District. Innovation entities within the industry have gathered into five principal clustering zones, including Suzhou International Science Park, major universities and institutions, the creative industrial zone, Suzhou High-Tech District Entrepreneurship Park, and High-Tech District Science City. The innovation-driving forces in the eastern region are not only more concentrated in terms of aggregation but also exhibit a higher level of quality. The spatial distribution pattern of innovation resource support is more balanced, extending its influence across the southern and northern parts of the city, thereby mitigating regional development imbalances. In contrast, the distribution of innovation environment quality revealed pronounced monocentric agglomeration and a concentric spillover pattern (Fig. 5c). This finding suggests that the location of innovation sources and carriers does not entirely depend on the existing built environment. Parcels located along the periphery of the main urban area and West Hill Island in Tai Lake, which are close to large green spaces and water bodies, exhibited weaker resource radiation, thus offering relatively lower support and attraction for innovation elements.

Characteristics of the urban spatial innovation potential. Spatial distribution mapping of the innovation potential within the main urban area of Suzhou (Fig. 6) revealed a notable multicentric polar region configuration. In the central area, there is an aggregation of approximately 62 plots with high innovation potential, resulting in a unique spatial pattern. This pattern is characterized by a singular core augmented by multiple nodal points and concentric layers of decreasing innovation intensity. The regions with notable innovation potential are distributed across four key areas: the old city area, the West Central Business District (CBD) of Jinji Lake, the East Higher Education Area of Dushu Lake, and Shishan Street. These areas demonstrate a clustering effect with close regional connections between each

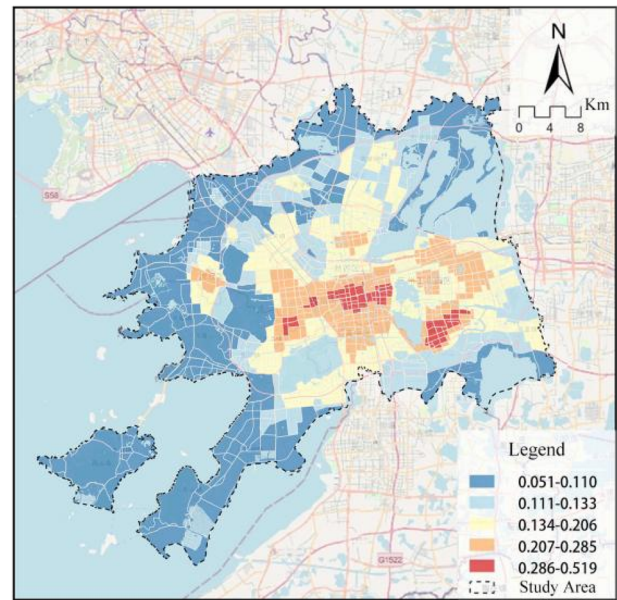


Fig. 6 Map of the characteristics of the urban innovation potential distribution. The map showing the multicentric distribution of innovation potential within Suzhou, highlighting decreasing intensity from the center to the periphery.

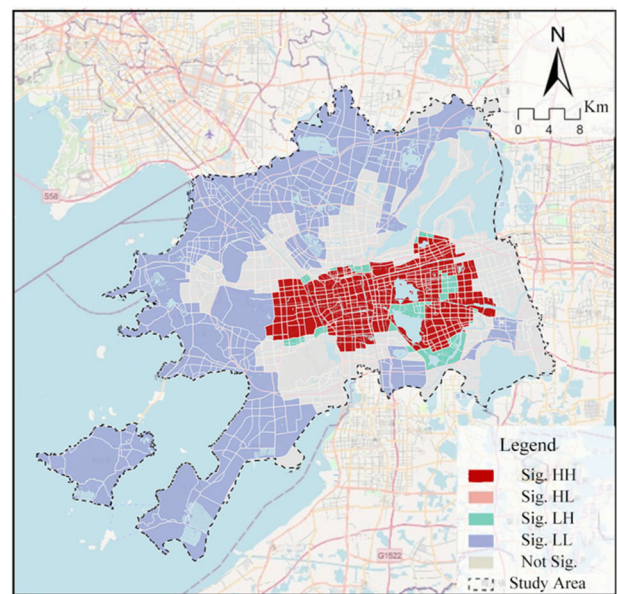


Fig. 7 LISA cluster map of the urban spatial innovation potential. The map showing spatial differences in innovation potential between core and peripheral areas, highlighting clustering regions and spatial continuity along key axes.

polar nucleus. The urban spatial innovation potential exhibits a concentric spatial trend of gradually decreasing from the center towards the periphery, indicating the diffusion of high innovation potential from the central area to low-innovation-potential areas at the edge of the urban area.

From a spatial analysis perspective, the innovation potential in the main urban area of Suzhou is concentrated along two main axes: an east-west corridor from High-Tech District Science City to the East Higher Education Area and a north-south corridor linking the Wuzhong District with the Xiangcheng District. Notably, the dissemination effect was greater along the east-west

corridor, thus highlighting horizontal expansion. These axes of innovation potential development, anchored by the city’s thoroughfares, serve a dual role: they facilitate cohesive linkages among various innovation nuclei and augment internal collaboration and synergy within the urban landscape.

The local indicators of spatial association clustering map clearly shows the spatial differences between core areas of innovation potential and their peripheral counterparts (Fig. 7). The global Moran’s I index is 0.7541, and the local Moran’s I is 0.840. Hotspots of the innovation potential were clustered primarily in the old city area and adjacent zones, with 332 parcels occurring in high-high clustering regions. Notably, clusters extended along Jinfeng South Road in the High-Tech Zone, reaching the Gusu District and continuing eastwards to Jinji Lake and Dushu Lake in the Industrial Park District. Overall, the notable spatial continuity among innovation potential hotspots suggests a well-dispersed and accessible distribution of essential innovation resources, including talent, capital, information, and services. Moreover, plots with nonsignificant innovation were mostly located along the periphery of the high-high clustering areas, while low-low clustering areas occurred at regional edges.

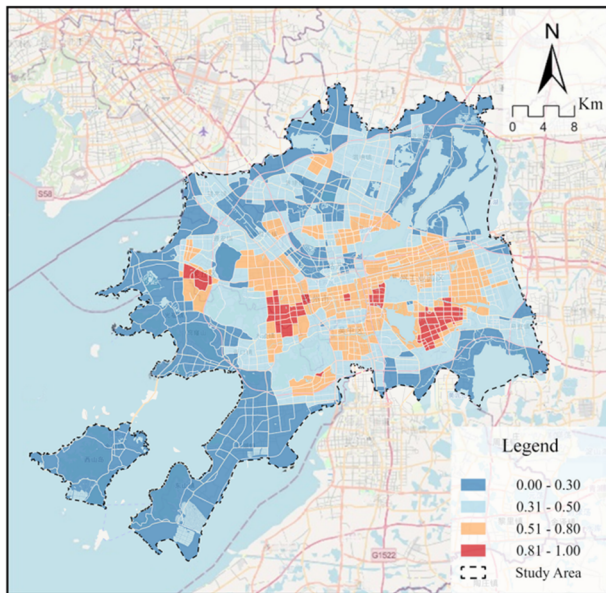


Fig. 8 Map of the spatial distribution of coupling coordination. The map reflects the interaction and synergy levels between innovation potential and innovation outputs in the study area.

The dense and continuous distribution of innovation hotspots indicates a high concentration in the main urban area of Suzhou, facilitating notable spatial interactions and spillover effects and creating a vibrant ecosystem for innovation citywide.

Coupling analysis of the innovation potential and innovation outputs. This research uses the CCDM to further explore the interaction and synergy levels between innovation potential and innovation outputs, quantitatively reflecting the association characteristics and conversion efficiency of their innovation attributes (Fig. 8).

The results showed that 287 plots exhibited discordant declines ($0 \leq D < 0.3$), largely concentrated along the urban periphery, indicating a need for improved interaction and coordinated development between innovation potential and innovation outputs. Additionally, two low-value clusters at the city center exhibited low coordination, with these plots often comprising residential and commercial lands surrounding wetland parks and large scenic areas. Approximately 35.39% of the plots occurred at a transitional development stage ($0.3 \leq D < 0.5$), indicating spatial heterogeneity. These plots were scattered across subcentral areas and regions undergoing industrial restructuring, with greater concentrations in southern areas than in northern areas. Approximately 29.12% of the plots occurred at a harmonized development stage ($0.5 \leq D < 0.8$) and were mainly distributed at the peripheries of high-value areas, suggesting that the regional innovation system is transitioning towards maturity, with the interaction between innovation potential and outputs approaching harmony. Although the number of plots exhibiting coordinated development ($0.8 \leq D \leq 1$) was limited, they demonstrated a notable multicentric innovation cluster effect, with four high-value clusters located in Shishan Street, Dushu Lake Higher Education Area, West CBD of Jinji Lake, and High-Tech District Science City. Their common characteristics include a concentration of higher education institutions and high-tech companies, covering fields such as medical devices, next-generation information technology, high-end intelligent manufacturing, and new energy, forming industry clusters with innovation capabilities.

Overall, innovation coordination in the main urban area of Suzhou exhibits a distribution pattern that diminishes from the center to the periphery. Among these, plots categorized under coordinated development (8.18%) are fewer in number but concentrated, displaying a clear innovation clustering effect. Plots at the transitional development (35.39%) and harmonized development (29.12%) stages dominate in terms of quantity, indicating that the overall innovation system is in a state of dynamic development, with some synergistic effects, although there remains significant room for improvement Table 7.

Table 7 Coupling and coordination between the innovation potential and innovation outputs.

Coupling coordination type	Coordination level	D value interval	Number of plots	Percentage	Total percentage
Discordant decline	Extreme incoordination	[0.0, 0.1]	96	9.13%	27.31%
	Severe incoordination	[0.1, 0.2]	69	6.57%	
	Moderate incoordination	[0.2, 0.3]	122	11.61%	
Transitional development	Moderate incoordination	[0.3, 0.4]	193	18.36%	35.39%
	Moderate incoordination	[0.4, 0.5]	179	17.03%	
Harmonized development	Moderate incoordination	[0.5, 0.6]	132	12.56%	29.12%
	Moderate incoordination	[0.6, 0.7]	108	10.28%	
	Intermediate coordination	[0.7, 0.8]	66	6.28%	
Coordinated development	Intermediate coordination	[0.8, 0.9]	37	3.52%	8.18%
	Excellent coordination	[0.9, 1.0]	49	4.66%	

Discussion

To systematically assess the urban spatial innovation potential, a structured evaluation framework was constructed on the basis of the SEM. The SEM enables the analysis of the interrelationships among latent variables. The results revealed that innovation-driving forces, innovation resource support, and innovation environment quality all positively affect urban spatial innovation potential. Serving as the origin and core driving force, innovation driving forces directly supply essential elements for innovation activities, including technology, knowledge, talent, and capital. This observation aligns with the findings reported by Breschi and Lissoni (2001). Notably, innovation-driving forces and innovation resource support indirectly enhance the quality of the urban environment, creating a positive feedback loop in which these components mutually reinforce and shape each other. The confluence of talent and technological advancements not only depends on resources and policy backing but also cultivates a favorable innovation environment, thereby attracting further talent and investments (Liu and Wang, 2023). Such interactive relationships ensure continuous optimization and improvement in urban spaces, resulting in holistic enhancement of urban innovation potential. In this context, Suzhou's launch of the "Eight Major Projects" for technological innovation in 2024, along with the support of "Several Policies for Fully Enhancing Technological Innovation Capabilities through the Implementation of the 'Eight Major Projects' in Suzhou," aimed to further strengthen these key elements. These policy measures are designed to further stimulate innovation dynamism, enrich the support of innovation resources, and enhance the quality of the innovation environment, thereby forming a stronger and more vibrant urban innovation ecosystem.

Significant spatial clustering and differentiation in the innovation potential, along with its determinants, mostly occur at distinct locations, thereby promoting innovation clusters (Krugman, 2009). The clustering phenomenon can be attributed to several factors. First, the intrinsic characteristics of innovation activities, which entail the preferential exchange of knowledge and technology transfer through networks and interactions (Ozman, 2008; Fitjar and Rodriguez-Pose, 2020), catalyze clustering within geographically contiguous regions, thus generating knowledge spillover effects (Vujanovic et al. 2022). Second, the high concentration of innovation resources, which include talent, capital, information, and technology, provides a robust external economy for enterprises and research institutions, facilitating the creation and application of new knowledge and technologies (Li and Du, 2022). Third, the targeted focus of governmental policies and investments in specific regions enhances this clustering effect (Porter, 2000; Martin and Ottaviano, 2001; Rodriguez-Pose and Crescenzi, 2008). With increasing geographical distance from the city center, the concentration of various resources and, correspondingly, the innovation potential exhibited a declining trend. Particularly in suburban regions, there is a pronounced tendency towards the concentration of manufacturing and conventional service industries (Li and Wang, 2019), characterized by lower innovation density and developmental velocity than those of core urban sectors (Shen, 2002). Although the flow of innovative elements could promote the influence of core areas and drive peripheral regions, it may also trigger a backflow effect (Myrdal, 1974), further strengthening the core area while weakening the peripheral regions.

This study revealed that the overall coordination between the innovation potential and innovation outputs in the main urban area of Suzhou remains at the transitional development stage, as determined by the CCDM. Although a trend towards coordination has begun to emerge between the two systems, they have not yet achieved a state of harmonious development. This finding

indicates that the existing innovation potential has not been fully transformed into outcomes, with actual innovation performance still falling short of expectations. Consequently, detailed strategies are urgently needed to enhance innovation development.

In 2020, Suzhou was officially designated the "China Industry-University-Research Cooperation Demonstration City" by the China Industry-University-Research Cooperation Promotion Association. Detailed observations of several high-coupling plots within Suzhou's main urban area reveal an interesting commonality: these areas typically form innovation development clusters through the aggregation of universities, research institutions, and innovation-driven enterprises. For example, Dushu Lake Higher Education Town not only hosts educational institutions such as Soochow University, Xi'an Jiaotong-Liverpool University, and the Industrial Park Vocational and Technical College, but also research institutions like the Suzhou Institute for Advanced Study, and the University of Science and Technology of China as well as high-tech enterprises such as Tengfei Innovation Park, Shenzhou Biotechnology Company, and Zhongmeng Intelligent Technology Company. This discovery strongly validates that industry-university-research cooperation is a core driving force in regional innovation development. On this basis, it is recommended to continue promoting collaborative innovation among multiple entities in industry, academia, and research at the strategic level. This can be achieved by providing tax incentives, research funding, and innovation subsidies to alleviate the risks and cost burdens for enterprises to engage in basic research (Peres et al. 2010). Additionally, it is crucial to actively encourage the establishment and strengthening of platforms and bridges for industry-university-research cooperation, such as technology transfer centers, industry-university-research alliances, and innovation workshops, to facilitate the transformation of academic research results and the rapid application of new technologies.

For the three types of areas that have not yet reached the stage of coordinated development, this paper proposes a series of targeted strategies based on detailed observations of the specific problems and needs at each stage.

- (1) **Discordant decline stage:** These areas are mainly located on the urban periphery and are often constrained by inefficient transportation networks and communication infrastructure, which limit the flow of information and talent, thereby hindering the accumulation and circulation of innovation resources. To address regional isolation, the government should consider implementing innovation special zone policies and providing targeted financial support and tax incentives to attract private capital and enterprises to settle in peripheral areas. Moreover, the possibility of remote innovation work models, such as mobile laboratories, temporary research and development centers, and other flexible forms of research and development support, should be explored to reduce geographical barriers and rapidly enhance innovation activity capabilities in peripheral areas.
- (2) **Transitional development stage:** Certain plots encounter spatial heterogeneity in innovation resource distribution, potentially resulting from historical path dependence and industrial layout imbalances. These conditions lead to local bottlenecks in innovation development (Gordon and McCann, 2005). For example, in the construction of the linked innovation zone in the Wuzhong District, experts have identified issues such as insufficient talent reserves, low enterprise synergy, and poor flow of production factors, which hinder the integrated development of innovation industry clusters. This situation may also result from unclear regional policy orientations or inadequate execution

of innovation policies. Relevant departments should implement targeted industrial upgrading policies and establish talent training systems that meet regional needs to attract and retain high-end talent (Muhsam, 1965). Furthermore, innovation demonstration zones in strategic areas should be established as models for integrating resources, guiding investment, and promoting technological collaboration, thereby improving the regional balance of innovation.

- (3) Harmonized development stage: The plots within this category, while exhibiting close connections between innovation resources and outputs, continue to struggle with low innovation conversion efficiency and insufficient market acceptance. According to the Suzhou Science and Technology Innovation Policy Assessment Report, while most innovation entities hold a positive view of Suzhou's overall financial innovation environment, a quarter of the respondents perceive the technical research environment as average or poor. Policymakers must enhance the legal framework for intellectual property rights to advance innovation activities and attract increased research and development investment (Moser, 2013). Additionally, policymakers should provide a clearer market orientation for innovation outcomes, support the commercialization of innovative products and services through measures such as government procurement, and offer guidance for the listing of innovative technologies (Lember et al. 2011).

Through the comprehensive strategies above, the objective is to effectively allocate and utilize the innovation resources within various plots, improving the efficiency of transforming innovation potential into actual outputs. Especially in promoting the implementation of the "Eight Major Projects," this study helps to identify three key types of mismatched plots between innovation output and innovation potential and provides data support for specific policy measures for these plots, thereby accelerating the spatial implementation of policies and the realization of their effects. Moreover, the establishment of a regular assessment mechanism for innovation resources and outputs could help in monitoring policy effectiveness and implementing necessary strategic adjustments to achieve coordinated development of the innovation system in the main urban area of Suzhou.

Conclusion

This study systematically investigates a quantitative measurement methodology for assessing innovation potential in urban spaces and applies it at the micro level to analyze the spatial distribution characteristics of innovation potential in Suzhou's main urban area. Furthermore, it evaluates the synergistic development between innovation potential and innovation outputs in this region, providing a comprehensive assessment and characterization of the interaction, symbiosis, and coexistence of innovation elements. The results indicate significant spatial agglomeration of innovation potential in the main urban area of Suzhou, characterized by a core-periphery pattern and decreasing diffusion from the center towards the periphery. However, the finding that fewer than 10% of the plots are highly coupled suggests that considerable room for improvement in innovation conversion efficiency.

At the methodological level, a novel application of the SEM in urban spatial innovation is introduced, demonstrating its effectiveness in evaluating complex interactions among multiple innovation variables, especially in addressing direct and indirect effects. The SEM enhances the precision and reliability of the results, providing robust methodological support for comprehensively evaluating urban innovation potential. Additionally, the CCDM is used to evaluate the interaction between innovation

potential and outputs and reveal regional imbalances and underutilized areas of innovation. As a systematic tool, this model can be used to assess and enhance regional innovation capacity, offering tailored recommendations through in-depth analysis of blocks at various stages of coupling coordination, thereby supporting urban innovation policy formulation and spatial resource allocation with scientific evidence.

This study also has limitations that can guide future research. First, the challenges in quantifying innovation in soft environments remain inadequately addressed. Although indicators such as co-working space density and nighttime light intensity indirectly reflect soft environmental factors, they do not fully capture the complexity of the industrial development atmosphere, policy regulations, and sociocultural aspects. Second, additional quantitative exploration is needed to investigate the factors influencing the innovation potential and industrial development in areas with low coupling coordination. Future studies should more comprehensively integrate diverse innovation theories and methods to increase the prediction accuracy and the understanding of innovation development factors. This paper provides a solid foundation for elucidating the multidimensional complexity of the urban spatial innovation potential and contributes fresh insights to both theory and practice in related fields.

Data availability

The datasets generated and analysed during the current study are not publicly available because they contain important patent-related information classified by the local government. However, the data are available from the corresponding author upon reasonable request and with permission from the relevant government authorities.

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References

- Acs ZJ, Anselin L, Varga A (2002) Patents and innovation counts as measures of regional production of new knowledge. *Res Policy* 31(7):1069–1085. [https://doi.org/10.1016/S0048-7333\(01\)00184-6](https://doi.org/10.1016/S0048-7333(01)00184-6)
- Adu-McVie R, Yigitcanlar T, Erol I, Xia B (2021) Classifying innovation districts: Delphi validation of a multidimensional framework. *Land Use Policy* 111:105779. <https://doi.org/10.1016/j.landusepol.2021.105779>
- Archibugi D, Pianta M (1996) Measuring technological change through patents and innovation surveys. *Technovation* 16(9):451–468. [https://doi.org/10.1016/0166-4972\(96\)00031-4](https://doi.org/10.1016/0166-4972(96)00031-4)
- Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. *Am Econ Rev* 86(3):630–640
- Babkin AV, Lipatnikov VS, Muraveva SV (2015) Assessing the impact of innovation strategies and R&D costs on the performance of IT companies. In: 11th International Strategic Management Conference, Vienna, AUSTRIA, Jul 23–25 2015. *Procedia Soc Behav Sci* pp 749–758. <https://doi.org/10.1016/j.sbspro.2015.10.153>
- Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Prog Hum Geogr* 28(1):31–56. <https://doi.org/10.1191/0309132504ph4690a>
- Boschma RA (2005) Proximity and innovation: a critical assessment. *Reg Stud* 39(1):61–74. <https://doi.org/10.1080/0034340052000320887>
- Breschi S, Lissoni F (2001) Localised knowledge spillovers vs. innovative milieu: Knowledge "tacitness" reconsidered. *Pap Reg Sci* 80(3):255–273. <https://doi.org/10.1007/pl00013627>
- Buchecker M, Frick J (2020) The implications of urbanization for inhabitants' relationship to their residential environment. *Sustainability* 12 (4). <https://doi.org/10.3390/su12041624>
- Button KJ (1976) Use of economics in urban travel demand modeling - survey. *Socio-Econ Plan Sci* 10(2):57–66. [https://doi.org/10.1016/0038-0121\(76\)90021-5](https://doi.org/10.1016/0038-0121(76)90021-5)
- Caragliu A, del Bo C, Nijkamp P (2009) Smart cities in Europe. Paper presented at the Cers 2009 - 3rd central european conference in regional science, international conference proceedings - young scientists articles,

- Carlsson B, Jacobsson S, Holmén M, Rickne A (2002) Innovation systems: analytical and methodological issues. *Res Policy* 31(2):233–245. [https://doi.org/10.1016/s0048-7333\(01\)00138-x](https://doi.org/10.1016/s0048-7333(01)00138-x)
- Chehabeddine M, Tvaronavičienė M, Vinogradova-Zinkevič I (2023) Measuring countries' performance in ecological security. *Acta Montan Slov* 28(3):603–620. <https://doi.org/10.46544/AMS.v28i3.07>
- Chen Q, Qian Q, Yao Z (2022a) Spatial patterns and regional organizational modes of urban innovation: case studies of Beijing, Shenzhen, and Shanghai. *City Plan Rev* 46(10):25–38
- Chen ZY, Dong BZZ, Pei Q, Zhang ZH (2022b) The impacts of urban vitality and urban density on innovation: evidence from China's greater Bay Area. *Habitat Int* 119. <https://doi.org/10.1016/j.habitatint.2021.102490>
- Cheng ML, Li Q, Wen ZG (2023) Coupling coordination degree analysis and driving factors of innovation network and eco-efficiency in China. *Environ Impact Assess Rev* 99. <https://doi.org/10.1016/j.ear.2022.107008>
- Cooke P, Uranga MG, Etxebarria G (1997) Regional innovation systems: institutional and organisational dimensions. *Res Policy* 26(4–5):475–491. [https://doi.org/10.1016/S0048-7333\(97\)00025-5](https://doi.org/10.1016/S0048-7333(97)00025-5)
- Crescenzi R, Nathan M, Rodríguez-Pose A (2016) Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Res Policy* 45(1):177–194. <https://doi.org/10.1016/j.respol.2015.07.003>
- Donoso JF (2017) A simple index of innovation with complexity. *J Informetr* 11(1):1–17. <https://doi.org/10.1016/j.joi.2016.10.009>
- Duan Y, Lu D, Bian L (2024) New method of evaluating spatial quality for innovation districts: a case study of Haidian and Chaoyang districts, Beijing. *Front Architect Res*. <https://doi.org/10.1016/j.foar.2024.09.002>
- Evans G (2009) Creative cities, creative spaces and urban policy. *Urban Stud* 46(5–6):1003–1040. <https://doi.org/10.1177/0042098009103853>
- Feldman MP, Florida R (1994) The geographic sources of innovation - technological infrastructure and product innovation in the united-states. *Ann Assoc Am Geogr* 84(2):210–229. <https://doi.org/10.1111/j.1467-8306.1994.tb01735.x>
- Fitjar RD, Rodríguez-Pose A (2020) Where cities fail to triumph: the impact of urban location and local collaboration on innovation in Norway. *J Reg Sci* 60(1):5–32. <https://doi.org/10.1111/jors.12461>
- Furman JL, Porter ME, Stern S (2002) The determinants of national innovative capacity. *Res Policy* 31(6):899–933. [https://doi.org/10.1016/s0048-7333\(01\)00152-4](https://doi.org/10.1016/s0048-7333(01)00152-4)
- Gao C, Cao MS, Wen Y, Li CQ (2023) Coupling and interaction between science and technology finance and green development: Based on coupling coordination degree model and panel vector autoregression model. *Front Environ Sci* 11. <https://doi.org/10.3389/fenvs.2023.1090998>
- Geng Y, Zhu H, Zhu R (2022) Coupling coordination between cultural heritage protection and tourism development: the case of China. *14 (22):15421*
- Gladevich J (2022) Assessment of the innovation potential of the regions of latvia, lithuania and belarus. *Entrep Sustain Issues* 10(1):293–327. [https://doi.org/10.9770/jesi.2022.10.1\(16\)](https://doi.org/10.9770/jesi.2022.10.1(16))
- Glaeser EL, Gottlieb JD (2006) Urban resurgence and the consumer city. *Urban Stud* 43(8):1275–1299. <https://doi.org/10.1080/00420980600775683>
- Gordon IR, McCann P (2005) Innovation, agglomeration, and regional development. *J Econ Geogr* 5(5):523–543. <https://doi.org/10.1093/jeg/lbh072>
- Griliches Z (1990) Patent statistics as economic indicators - a survey. *J Econ Lit* 28(4):1661–1707. <https://doi.org/10.3386/w3301>
- Gu Z (2023) Research on the impact of deep integration of industrial chain and innovation chain on the efficiency of innovation resources utilization. *Sustain Dev* 13(03):975–989. <https://doi.org/10.12677/sd.2023.133103>
- Hall BH, Jaffe A, Trajtenberg M (2005) Market value and patent citations. *Rand J Econ* 36(1):16–38
- Hamidi S, Zandiatashbar A (2019) Does urban form matter for innovation productivity? A national multi-level study of the association between neighbourhood innovation capacity and urban sprawl. *Urban Stud* 56(8):1576–1594. <https://doi.org/10.1177/0042098018767002>
- He YZ, Wang Y, Quan CG (2024) Coupled coordination and drivers of green technology innovation and carbon emission efficiency. *Sustainability* 16 (7). <https://doi.org/10.3390/su16072710>
- Hutton TA (2006) Spatiality, built form, and creative industry development in the inner city. *Environ Plan Econ Space* 38(10):1819–1841. <https://doi.org/10.1068/a37285>
- Inkinen T, Kaakinen I (2016) Economic geography of knowledge-intensive technology clusters: lessons from the Helsinki metropolitan area. *J Urban Technol* 23(1):95–114. <https://doi.org/10.1080/10630732.2015.1090196>
- Jaffe AB (1989) Real effects of academic research. *Am Econ Rev* 79(5):957–970
- Jiang T (2014) Spatial differentiation and its influencing factors of regional innovation output in Zhejiang province. *Geogr Res* 33(10):1825–1836
- Jurowetzki R, Lema R, Lundvall B-A (2018) Combining innovation systems and global value chains for development: towards a research agenda. *Eur J Dev Res* 30(3):364–388. <https://doi.org/10.1057/s41287-018-0137-4>
- Kline RB (2018) Response to Leslie Hayduk's review of principles and practice of structural equation modeling, 4th edition. *Can Stud Popul* 45(3–4):188–195. <https://doi.org/10.25336/csp29418>
- Krugman P (1991) Increasing returns and economic geography. *J Polit Econ* 99(3):483–499. <https://doi.org/10.1086/261763>
- Krugman P (2009) The increasing returns revolution in trade and geography. *Am Econ Rev* 99(3):561–571. <https://doi.org/10.1257/aer.99.3.561>
- Lee YS (1996) Technology transfer' and the research university: a search for the boundaries of university-industry collaboration. *Res Policy* 25(6):843–863. [https://doi.org/10.1016/0048-7333\(95\)00857-8](https://doi.org/10.1016/0048-7333(95)00857-8)
- Lember V, Kalvet T, Kattel R (2011) Urban competitiveness and public procurement for innovation. *Urban Stud* 48(7):1373–1395. <https://doi.org/10.1177/0042098010374512>
- Li D, Wei YD, Wang T (2015) Spatial and temporal evolution of urban innovation network in China. *Habitat Int* 49:484–496. <https://doi.org/10.1016/j.habitatint.2015.05.031>
- Li J, Zhang W, Ma R, Ma X, Yu J (2016) Analysis framework and application of urban innovation space potential: a case study of Hangzhou. *Econ Geogr* 36(12):224–232. <https://doi.org/10.15957/j.cnki.jjdl.2016.12.032>
- Li JA, Li YC, Tu MY, Liu XJ (2024) Third places as catalysts for technological innovation? Evidence from a grid cell level analysis of Nanjing, China. *Int J Urban Sci* 28(1):105–123. <https://doi.org/10.1080/12265934.2023.2216674>
- Li Y (2023) The changing spatialities of China's knowledge economy: introduction to the special issue. *Int J Urban Sci* 27(3):345–354. <https://doi.org/10.1080/12265934.2023.2229807>
- Li Y, Du R (2022) Polycentric urban structure and innovation: evidence from a panel of Chinese cities. *Reg Stud* 56(1):113–127. <https://doi.org/10.1080/00343404.2021.1886274>
- Li Y, Liu X (2018) How did urban polycentricity and dispersion affect economic productivity? A case study of 306 Chinese cities. *Landscape Urban Plan* 173:51–59. <https://doi.org/10.1016/j.landurbplan.2018.01.007>
- Li Y, Tang YK, Wang K, Zhao QW (2019) Environmental regulation and China's regional innovation output-empirical research based on spatial Durbin model. *Sustainability* 11 (20). <https://doi.org/10.3390/su11205602>
- Li Y, Wang X (2019) Innovation in suburban development zones: evidence from Nanjing, China. *Growth Change* 50(1):114–129. <https://doi.org/10.1111/grow.12270>
- Li Y, Xiong W, Hu X (2023) The geography of intercity technological proximity: evidence from China. *Int J Urban Sci* 27(3):355–370. <https://doi.org/10.1080/12265934.2021.1938641>
- Lim U (2003) Knowledge spillovers, spatial dependence, and regional economic growth in United States metropolitan areas <https://repositories.lib.utexas.edu/items/b7c1acc-55c0-4f96-8beb-a4871f690c76>
- Lin J, Liu J, Liu P (2019) Regional innovation capabilities and potentials evaluation: a case study of the pearl river delta national independent innovation demonstration zone. *J Urban Stud* 46:60–68
- Liu D, Li C (2024) Coupling coordination and spatial-temporal evolution between high-quality development of construction industry and scientific and technological innovation. *Environ Dev Sustain*. <https://doi.org/10.1007/s10668-024-04784-2>
- Liu LYQ, Zhang YX, Zhang J, Zhang SQ (2020) Coupling coordination degree of government support, financial support and innovation and its impact on economic development. *IEEE access* 8:104039–104051. <https://doi.org/10.1109/ACCESS.2020.2999501>
- Liu S, Wang W (2023) Research on the generating mechanism of urban talent competitiveness based QCA method: a configurational analysis of 24 Chinese cities. *Sustainability* 15 (7). <https://doi.org/10.3390/su15076120>
- Lu Z, Li H, Wei X, Tang Y, Yin Z, Yin P (2022) Evaluation and influencing factors of scientific and technological innovation potential in core areas of urban agglomerations: taking the core area of Changsha-zhuzh-Xiangtan urban agglomeration as an example. *Econ Geogr* 42(4):141–149
- Luo Y, Chan RCK (2020) Production of coworking spaces: evidence from Shenzhen, China. *Geoforum* 110:97–105. <https://doi.org/10.1016/j.geoforum.2020.01.008>
- Ma Y, Wang L, Hu D, Ge Y, Zuo J, Lan T (2023) Analysis of spatial patterns of technological innovation capability based on patent data in Jiangsu province, China. *Humanit Soc Sci Commun* 10 (1). <https://doi.org/10.1057/s41599-023-02428-w>
- MacPherson AD (1997) A comparison of within-firm and external sources of product innovation. *Growth Change* 28(3):289–308
- Mariotti I, Akhavan M, Rossi F (2023) The preferred location of coworking spaces in Italy: an empirical investigation in urban and peripheral areas. *Eur Plan Stud* 31(3):467–489. <https://doi.org/10.1080/09654313.2021.1895080>
- Martin P, Ottaviano GIP (2001) Growth and agglomeration. *Int Econ Rev* 42(4):947–968. <https://doi.org/10.1111/1468-2354.00141>
- McNeill D (2021) Urban geography 1: 'gig tech' and the reshaping of urban space. *Prog Hum Geogr* 45(5):1311–1319. <https://doi.org/10.1177/03091325211021945>
- Meijer A, Thaens M (2016) Urban technological innovation. *Urban Affairs Review* 54. <https://doi.org/10.1177/10780874166670274>
- Morgan K (2004) The exaggerated death of geography: learning, proximity and territorial innovation systems. *J Econ Geogr* 4(1):3–21. <https://doi.org/10.1093/jeg/4.1.3>

- Moser P (2013) Patents and innovation: evidence from economic history. *J Econ Perspect* 27(1):23–44. <https://doi.org/10.1257/jep.27.1.23>
- Muhsam HV (1965) Human capital, a theoretical and empirical analysis with special reference to education. In: *Revue De L Institut International De Statistique-Review of the International Statistical Institute*, 33:3. <https://doi.org/10.2307/1401709>
- Myrdal G (1974) Contribution to more realistic theory of economic growth and development. *Trimest Econ* 41(161):217–229
- Nasir A, Zakaria N, Zien Yusoff R (2022) The influence of transformational leadership on organizational sustainability in the context of industry 4.0: mediating role of innovative performance. *Cogent Bus Manag* 9 (1). <https://doi.org/10.1080/23311975.2022.2105575>
- Niu Q, Wang G, Liu B, Zhang R, Lei J, Wang H, Liu M (2023) Selection and prediction of metro station sites based on spatial data and random forest: a study of Lanzhou, China. *Sci Rep*. 13(1):22542. <https://doi.org/10.1038/s41598-023-49877-6>
- Ozman M (2008) Network formation and strategic firm behaviour to explore and exploit. *J Artif Soc Soc Simul* 11 (1)
- Pan Y, Weng G, Li C, Li J (2021) Coupling coordination and influencing factors among tourism carbon emission, tourism economic and tourism innovation. *Int J Environ Res Public Health* 18 (4):1601
- Peres R, Muller E, Mahajan V (2010) Innovation diffusion and new product growth models: a critical review and research directions. *Int J Res Mark* 27(2):91–106. <https://doi.org/10.1016/j.ijresmar.2009.12.012>
- Perroux F (1963) 2 Sector-model of innovation-expenditures - low-growth and high-growth rates. *Econ Appl* 16(4):503–560
- Ponta L, Puliga G, Manzini R (2021) A measure of innovation performance: the Innovation Patent Index. *Manag Decis* 59(13):73–98. <https://doi.org/10.1108/md-05-2020-0545>
- Porter ME (1998) Clusters and the new economics of competition. *Harv Bus Rev* 76(6):77
- Porter ME (2000) Location, competition, and economic development: local clusters in a global economy. *Econ Dev Q* 14(1):15–34. <https://doi.org/10.1177/089124240001400105>
- Qamruzzaman M (2021) Do international capital flows, institutional quality matter for innovation output: the mediating role of economic policy uncertainty. *Green Financ* 3(3):351–382. <https://doi.org/10.3934/GF.2021018>
- Qiu J, Liu Y, Yuan L, Chen C, Huang Q (2020) Mapping the micro-scale scientific and technological innovation potentials of Guangdong-Hong Kong-Macao Greater Bay Area: a response to spatial planning. *Trop Geogr* 40(5):808–820
- Rodriguez-Pose A, Crescenzi R (2008) Research and development, spillovers, innovation systems, and the genesis of regional growth in Europe. *Reg Stud* 42(1):51–67. <https://doi.org/10.1080/00343400701654186>
- Roper S, Hewitt-Dundas N (2015) Knowledge stocks, knowledge flows and innovation: evidence from matched patents and innovation panel data. *Res Policy* 44(7):1327–1340. <https://doi.org/10.1016/j.respol.2015.03.003>
- Rosenthal SS, Strange WC (2003) Geography, industrial organization, and agglomeration. *Rev Econ Stat* 85(2):377–393. <https://doi.org/10.1162/003465303765299882>
- Shearmur R, Doloreux D (2009) Place, space and distance: towards a geography of knowledge-intensive business services innovation. *Ind Innov* 16(1):79–102. <https://doi.org/10.1080/13662710902728001>
- Shen JF (2002) The spatial economy: cities, regions and international trade. *Urban Geogr* 23(8):794–795. <https://doi.org/10.2747/0272-3638.23.8.794>
- Sun LY, Wang ZY, Yang L (2023) Research on the dynamic coupling and coordination of science and technology innovation and sustainable development in Anhui province. *Sustainability* 15 (4). <https://doi.org/10.3390/su15042874>
- Sun Y, Li M, Hong Z, Runlian M (2020) Research on the construction of regional innovation service platform resource system based on innovation ecosystem. *China Sci Technol Resour Guide* 52(03):1-8+85
- Venegas H, Prudant E (2021) Industrial activity in the socio-spatial configuration of the Yungay neighborhood, 1930-1950. *Rev INVI* 36(101):256–282. <https://doi.org/10.4067/s0718-83582021000100256>
- Vernon R (1966) International investment and international trade in product cycle. *Q J Econ* 80(2):190–207. <https://doi.org/10.2307/1880689>
- Vujanovic N, Radosevic S, Stojic N, Hisarcikilar M, Hashi I (2022) FDI spillover effects on innovation activities of knowledge using and knowledge creating firms: evidence from an emerging economy. *Technovation* 118. <https://doi.org/10.1016/j.technovation.2022.102512>
- Wang J, Liu NN (2020) Empirical study on the evaluation of urban innovation space development potential in 9 districts of Hangzhou. *Econ Geogr* 40(11):105–111
- Wang Q, Pei XJ, Liang HG (2022) Founder CEO, CEO characteristics, and firm innovation efficiency: an empirical study of China's GEM-listed companies. *Sustainability* 14 (14). <https://doi.org/10.3390/su14148250>
- Wang Z, Wang X, Yan J (2020) The logic and thought of innovation space evolution of high-quality urban development. *Urban Stud* 27(8):51–58
- Wen F, Yang S, Huang D (2023) Heterogeneous human capital, spatial spillovers and regional innovation: evidence from the Yangtze River Economic Belt, China. *Humanit Soc Sci Commun* 10(1):365. <https://doi.org/10.1057/s41599-023-01809-5>
- Wijngaarden Y, Hitters E, Bhansing PV (2020) Cultivating fertile learning grounds: collegiality, tacit knowledge and innovation in creative co-working spaces. *Geoforum* 109:86–94. <https://doi.org/10.1016/j.geoforum.2020.01.005>
- Wu K, Wang Y, Zhang H, Liu Y, Ye Y (2021) Impact of the built environment on the spatial heterogeneity of regional innovation productivity: evidence from the Pearl River Delta, China. *Chin Geogr Sci* 31(3):413–428. <https://doi.org/10.1007/s11769-021-1198-4>
- Yang J, Liu W, Liu Z (2024) Theoretical progress and prospects of regional innovation research. *Prog Geogr* 43(2):361–373
- Zhang FQ, Wang Y, Liu W (2020) Science and technology resource allocation, spatial association, and regional innovation. *Sustainability* 12 (2). <https://doi.org/10.3390/su12020694>
- Zhong X, Li Y (2024) Does micro-geographical proximity matter for knowledge spillovers? Evidence from the quasi-natural experiment of university relocation in China. *Appl Geogr* 173:103449. <https://doi.org/10.1016/j.apgeog.2024.103449>
- Zhu K, Xu J, Wang X (2023) The evolution of urban innovation space and its spatial relationships with talents' living demands: evidence from Hangzhou, China. *Int J Urban Sci* 27(3):442–460. <https://doi.org/10.1080/12265934.2022.2085153>
- Zucker LG, Darby MR, Brewer MB (1998) Intellectual human capital and the birth of US biotechnology enterprises. *Am Econ Rev* 88(1):290–306
- Zukin S (2021) Planetary Silicon Valley: deconstructing New York's innovation complex. *Urban Stud* 58(1):3–35. <https://doi.org/10.1177/0042098020951421>

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Author contributions

L.H. and W.S. conceptualized the study, collected the data, and conducted the analyses. W.S., L.H., and H.M. designed, structured, and wrote the paper. W.S., L.H., L.Y., and H.M. contributed to manuscript editing.

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants or animals.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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