International Journal of Geo-Information

Article

Delineating and Typologizing Urban Innovation Districts Beyond Administrative Boundaries Using Multi-Source Geospatial Data: Evidence from Shanghai

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Abstract

Urban innovation districts (UIDs) provide an important space for innovation-led development. However, their scale and the heterogeneity within the districts are not easy to capture with administrative units, especially in urban centers of great denseness. Therefore, we develop a parcel-based geospatial framework to locate and typify the UIDs in Shanghai using multi-source geospatial data. Morphology parcels are used to measure an innovation asset index, and a hierarchical density-based spatial clustering algorithm (HDBSCAN) is applied to identify functionally coherent innovation agglomerations beyond administrative boundaries. The procedure identifies 18 UIDs; an exploratory stability check further indicates that high-value core parcels are largely retained under moderate density-connectivity perturbations, whereas peripheral boundary parcels are more sensitive. Patent-density and policy-alignment evidence are used as supporting external evidence for the delineated innovation geography and as one part of a convergent evidence check. To describe spatial heterogeneity, we collate 31 conceptual indicators, operationalized as 38 PCA variables after dummy coding, to represent locational features, urban form, function and environmental quality. Principal component analysis reduces these variables to six components explaining 81.59% of the total variance, and hierarchical clustering classifies the districts into five types. A k = 2–8 cluster-quality assessment supports the five-type solution as a balanced and interpretable classification rather than a uniquely optimal statistical partition. The results reveal mismatches between administrative boundaries and functional innovation spaces, as well as systematic built-environment differences across district types.

Keywords: urban innovation districts; geospatial analysis; spatial delineation; clustering; spatial typology

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Academic Editors: Wolfgang Kainz, Shivanand Balram, Eric Vaz and Suzana Dragicevic

Received: 16 April 2026
Revised: 12 June 2026
Accepted: 22 June 2026
Published: 1 July 2026

1. Introduction

Innovation-based development is crucial to many contemporary cities and has transformed the organization of land use, infrastructure, knowledge assets and so on [1,2]. For this agenda of development, innovation districts emerge as space nodes that link spatial governance to economic restructuring [3,4]. In line with international references such as the Boston Seaport District, innovation districts are 'not only places for industrial clusters [but] also an infrastructural combination of social and spatial processes aimed at encouraging knowledge spill over through physical proximity and urban access to amenities' [5–7].

Despite global proliferation, scholars' understanding of innovation districts is scarce in two important respects, particularly from a land-use perspective [8–10]. First, existing typologies tend to be rather functional and qualitative [11,12]. Many influential typologies, like the Brookings Institution's "anchor-plus" model, focus on institutional conditions but fail to understate the role of the spatial form [13,14]. Walkability, density, street morphology and access to amenities can shape face-to-face interaction, knowledge spillovers and place attractiveness; however, empirical studies that integrate such built-environment indicators with geocoded innovation activity remain comparatively limited [15,16].

Consequently, there is a relative scarcity of quantitative evidence on how particular physical forms spatially link to innovation activities [16,17]. Second, state-based and high-density urban environment empirical evidence are insufficient [18]. Most studies focus on market-driven models in the West economies [19]. However, in the emerging economies of China, the formation of innovation space is heavily influenced by the combination of rigid land use regulations, top-down industrial policy and local state entrepreneurship [20–22]. This particular context causes spatial mismatches between administrative planning boundaries and actual agglomeration of innovation activities [23,24]. Understanding such distinctive spatial logics is critical for proper urban land policy in the backdrop of fast-urbanizing contexts.

Along with these gaps, this study also builds a framework based on several urban data sources to identify, characterize, and classify the urban innovation districts, using Shanghai as an empirical case. In this study, we aim to: (1) provide a bottom-up identification method of innovation districts based on geospatial clustering of the granular innovation data to locate the de facto boundary of the innovation districts; (2) establish a comprehensive built-environment indicator system for measuring the morphological and functional traits that influence innovation performance; and (3) induce a new type through PCA and HCA based on empirical facts, to target land use plan. By identifying the heterogeneity of innovation districts, this study offers practical advice for the allocation of land resources matching the development stage of innovation ecosystems.

2. Related Works

2.1. Evolution of Urban Innovation Districts: Concepts, Definitions, and Determinants

Since Schumpeter first observed innovation as an engine of economic development, scholarly research has moved beyond the firm to study industry, regional and urban dynamics [25,26]. The evolution has drawn attention to the role of knowledge spillovers, environments, institutions and collaboration in shaping innovation performance [27–29]. As KBUD has emerged, innovation has become the key structuring logic of urban development [30,31]. That change has led to the emergence of a new spatial form: the urban innovation district [32]. Innovation districts are mixed-use areas deliberately constituted by public and private entities to draw, attach, and scale innovative activities [33,34].

They have served as sites for urban regeneration, and they are key local nodes in creative growth-based economic development [35]. Innovation districts, therefore, are not just economic developments, but strategic interventions in urban land use, requiring zoning, infrastructure investments and spatial planning.

Evolution of innovation districts also links to a longer lineage of innovation-oriented forms of urban space [36]. Earlier forms, such as industrial districts and suburban science parks, proximised research, production and technological activities but operated under different spatial and organizational logics [37–39]. Industrial districts of nineteenth and twentieth centuries were groundlinked to labor supply and production capacity [40,41]. By contrast, post-war science parks emerged from decentralized and car-dependent development patterns, and were mostly closed R&D institutions [42]. Current innovation districts deviate from earlier forms in being situated in inner cities or along transit corridors. They take openness, knowledge transfer and networked, mixed uses to the city [3].

Related concepts share similar institutional or economic aspects, but innovation districts uniquely stand out with their combination of urban form, land use mix and spatial governance. Across various contexts, many defining features consistently characterize innovation districts. First, they house dense, heterogeneous innovation economies that cohabit universities, research centers, established firms, start-ups, incubators and accelerators [43,44]. They are usually built on compact, walkable urban form, with strong multimodal accessibility and advanced digital connectivity that favor a high intensity of research and commercial activities in a polyfunctional urban context [45,46]. The spatial developmental tendency of such districts reflects broader dynamics of the geography of innovation in terms of how proximity, connectivity and openness increasingly underpin the competitive urban innovation capacity.

Research has established several specific characteristics of innovation districts. They are dense innovation ecosystems that congregate universities and research institutes, major firms, start-ups, incubators, and accelerators [44,47]. The built environment of innovation districts is generally compact, walkable, multimodal access-focused, and digitally advanced for carrying out high-productivity research and business activities across a multifunctional urban landscape [45]. The evolution of innovation districts reflects the evolution in the geography of innovation as proximity, connectivity, and openness increasingly come to support innovation capacity in urban environments.

Recent research also makes the catalytic nature of density, accessibility, digital connectivity, and mixed land use patterns evident for encouraging face-to-face interactions, knowledge exchange, and serendipity [48–50]. Brief street grids increase pedestrian connectivity and ease coordination friction, enabling the network mobilization necessary for networking and very early ventures to take place [51,52]. Built-form indicators such as density of employment, road network configuration, and proximity to amenities are also associated with innovation-related activities [53]. In addition, informal social infrastructures play the role of third places in nurturing weak ties and facilitating the interpersonal encounters that are important for innovation [54].

With these insights, however, there are substantial gaps in the empirical characterization and mapping of innovation districts. There is empirical evidence of the inter-play of physical, institutional, economic, social and cultural forces for innovation districts [8,9], but the systematic embedding of the finer characteristics of morphology into the characterization and measurement of innovation districts is lacking [55]. The limitation reduces both the fine-grained precision with which innovation districts can be mapped and the theoretical precision with which innovation districts are understood [8]. In growing, transformational cities such as Shanghai, these gaps restrict opportunities for attaining robust, scalable and context-sensitive ways of identifying and analyzing emerging innovation geographies [56].

2.2. International Typologies, Spatial Morphology and Comparative Frameworks

International experiences provide considerable diversity in the morphology, governance models and developmental processes of innovation districts [32]. For example, classical innovation districts such as Silicon Valley and Sophia Antipolis are early suburban technology parks featuring low density, car-connected accessibility and closed innovation typology [57,58]. More recent examples, such as Barcelona's 22@ district, Helsinki's Arabianranta, and Singapore's One-North are a more urbanized, mixed-use, and transit-orientated form of innovation districts [1]. All these examples are examples of a move away from single-purpose periphery research hubs to more open, mixed-use and dense innovation districts, where the demarcation of work, living and leisure is blurred [59].

Typological studies have also tried to capture this diversity systematically. The most influential typology comes from the Brookings Institution. They divide innovation districts into three models: (1) Anchor Plus districts, centered around large research institutions and mixed-use redevelopment; (2) re-imagined urban districts, a term for changing old industrial or waterfront districts; and (3) urbanized science parks, essentially the densification and urbanization of originally suburban R&D sites. Although influential, the models are largely created by agents and functions; in the end, quantitative capture of physical form (e.g., block size, street connectivity, building density) is relatively abstract.

Other frameworks complement this institutional perspective. Research on small and medium-sized high-technology precincts also suggests that innovation districts can vary according to planning regimes and physical design features [3,60]. More recent work expands on this line of enquiry through multidimensional and performance-based classifications that include economic, governance and spatial indicators [61]. Building on these contributions, some reviews underline the relevance of a holistic approach that integrates functional features, morphological features and patterns of use in space [62,63]. Such approaches seek to capture more comprehensively the complex socio-spatial dynamics that shape innovation districts in modern cities.

Despite these advances, however, several caveats remain. Most of the existing typologies are conceptual or descriptive in nature and not empirically derived [64]. Frameworks developed for Western or post-industrial cities are not necessarily applicable to a more high-density, state-oriented development context, such as that found in China [65]. Furthermore, prevailing categories provide weak insights on hybrid development forms [66]. They include districts that have a mix of research-intensive functions and headquarters economies, or that are determined by strong government's intervention and lands appropriation. All the above limitations point to a more systematic and empirical approach to categorization [67]. Such an approach should be able to capture fine-grained regional spatial heterogeneities, as well as the distinct institutional arrangements for innovation districts in an urban context that is experiencing a dramatic structural transformation.

2.3. Data-Driven Methods of Delineation and Classification

Over the past few years, methodologies to delineate innovation districts have seen rapid developments. Initial approaches mainly used administrative boundaries or planning-designated locations that usually do not reflect functional innovation geography [68]. With the development of urban big data, more recent work shifts to a data-driven approach based on multi-source geospatial data and machine-learning techniques to detect spatial aggregation patterns of innovation [69–71].

Accurate identification of innovation districts requires appropriately tackling the statistical properties of urban data. Innovation-related indicators such as patent activity, density of firms or density of employment are not normally distributed, but rather have a heavy-tailed distribution [72]. In this case, the natural breaks or quantile classifications often mask a hierarchical structure [73]. Fractal approaches (specifically, the head and tail breaks) have therefore been proposed as the most natural and robust way to detect dense spots before clustering [74].

On this basis, density-based clustering algorithms are typically used to delineate innovation districts. Methods such as DBSCAN and its hierarchical extension HDBSCAN allow for clustering of different density levels and always explicitly detect noise points [75,76]. Compared with partition-based clustering methods such as k-means, density-based methods are more suitable for this study because innovation activities in Shanghai are polycentric, density-heterogeneous, and irregular in spatial shape. K-means requires the number of clusters to be specified in advance and tends to produce compact partitions. SKATER and related regionalization methods are useful for identifying local spatial relationships under adjacency constraints, but they are more suited to partitioning contiguous spatial units into internally coherent regions [77]. HDBSCAN is therefore adopted because it can identify clusters with irregular shapes and varying densities while explicitly treating weakly connected observations as noise.

After delineation of innovation districts, there are typically classification methods used to account for its internal diversity. At this level, multivariate statistical methods play a key role in structuring complex data and detecting latent spatial and functional patterns [78]. PCA is broadly used to reduce high-dimensional built-environment dataset into a small set of orthogonal components accounting for the dominant spatial structure [79]. To make a clearer interpretation, CBA can serve as an interpretive tool to summarize the contribution of each component [80]. HCA is commonly used to separate innovation districts into classes using the scores of each component, maintaining hierarchical information, as well as allowing for easy visual diagnostic measures [24,81].

There is growing evidence in recent studies that an integrated scheme that combines fractal-based thresholding, density-based spatial clustering and multivariate typological analysis provides a rigorous and transparent way of defining and classifying innovation districts. This kind of scheme provides rigor and clarity for field studies in complex and rapidly changing urban environments.

2.4. Summary of Research Gaps and Theoretical Positioning

Although the literature on innovation districts has burgeoned, gaps exist. Much of the existing conceptual and typology literature has been developed in Western countries or post-industrial cities, so it is not well equipped to capture innovation districts emerging in high-density or state-driven urban development environments such as China [82,83]. In addition, built-environment morphology is rarely analyzed systematically and operationally at all, despite building evidence for the effect of built environment on innovation [84]. Key spatial characteristics of the built environment, such as density, mix of land use, block structure and street-network configuration, are often described rather than treated as measurable, analytical attributes.

Methodological limitations also limit what is known from current research. Many typologies are still fairly qualitative, lacking empirical bases or indicators for cross-city comparison [85]. Delineation methods using administrative boundaries also favor mismatches between formal planning units and the functional geography of innovation activity, often misleading local land-use and policy choices [86]. Few studies combine multi-source data on cities with advanced spatial delineation and classification methods to delineate and explain patterns of innovation districts.

Against this background, this study contributes to: (1) bringing together morphological and functional factors into a single analytical framework; (2) using head/tail breaks and DBSCAN to identify innovation districts from multiple data source urban data in a density-heterogeneous mega city; (3) constructing an exploratory data-driven type profile via PCA and HCA, supported by additional cluster-quality diagnostics; and (4) extending innovation district theory by exploring Shanghai as a typical but as yet insufficiently considered region in non-Western cities. This positions the study to advance a more general, more spatial, more parsimonious understanding of how innovation districts arise, differentiate and develop in rapidly changing cities.

3. Methodology

To develop a rigorous and transferable process for the spatial delineation and interpretation of innovation districts, this study proposes a generalized analytical workflow based on multi-source urban data (Figure 1). The framework integrates spatial identification, pattern characterization, and typological interpretation into a coherent process. The empirical context of Shanghai is introduced separately in Section 3.1 and subsequent figure.

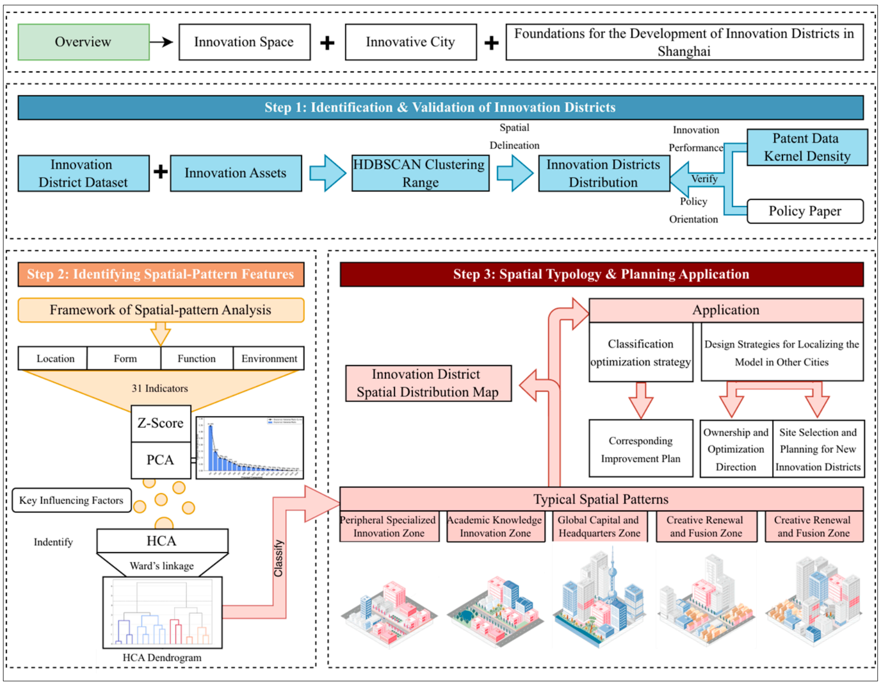

Figure 1. The workflow of this research.

The first phase focuses on delineating the spatial distribution of innovation districts. Street blocks are used as the basic spatial units to capture the fine-scale distribution of innovation activities. Innovation-activity indicators are assigned to street blocks, standardized, and aggregated to generate a continuous surface of innovation intensity. Kernel density estimation and the head/tail breaks method are then applied to identify hierarchical concentration patterns in the resulting heavy-tailed distribution. Based on this thresholding process, HDBSCAN is used to identify spatial clusters with varying densities and to distinguish dense innovation agglomerations from weakly connected or scattered observations. This procedure enables innovation districts to be delineated beyond administrative boundaries.

The second phase characterizes and classifies the identified clusters. A multidimensional indicator system is developed to capture their spatial, functional, and environmental characteristics. Thirty-one conceptual indicators, operationalized as thirty-eight variables after dummy coding categorical measures, are selected to describe the location, urban form, functional composition, and environmental conditions. These variables are standardized and dimensionally reduced using principal component analysis (PCA), and the resulting component scores are further classified through hierarchical cluster analysis (HCA) to reveal latent spatial typological structures.

The third phase translates the derived spatial typologies into planning-oriented interpretation and application. To improve the analytical transparency, we also report exploratory stability and cluster-quality diagnostics, and use patent- and policy-based comparisons as supporting evidence rather than as definitive proof of the typological classification.

3.1. Study Area

Shanghai is chosen as the empirical setting of our study due to its strategic position as a Global Science and Technology Innovation Centre and its high density and polycentric urban form. These features make Shanghai a typical case for studying innovation districts in non-Western cities [87]. Situated in the Yangtze River Delta (Figure 2a), the city is constituted by a compact core surrounded by five new towns developed through strategic and comprehensive development policies (Figure 2b), with the complex pattern of innovation activity shaped by intensive land use and overall development policies.

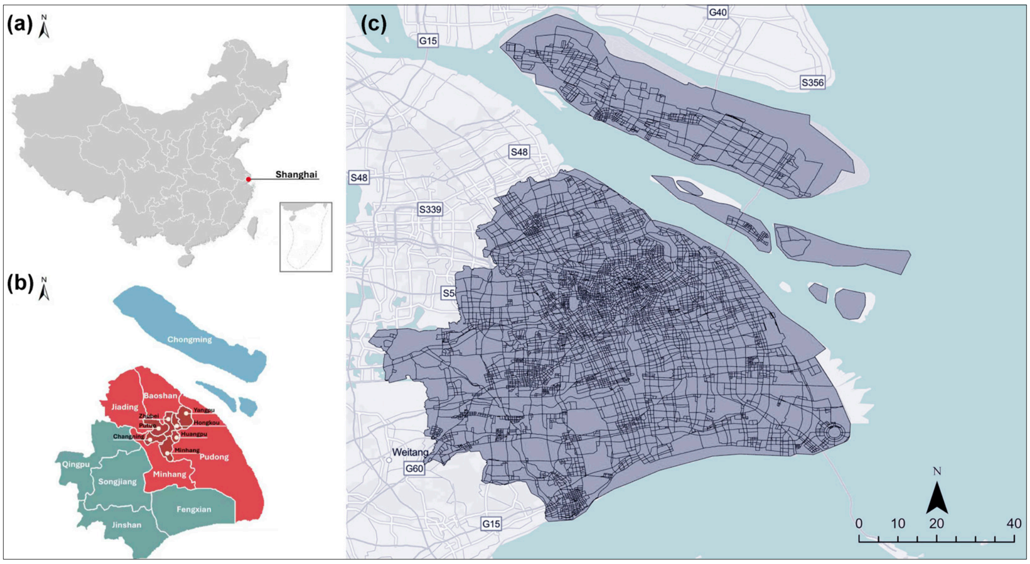

Figure 2. Study area and spatial analysis units. (**a**) Location of Shanghai within China; (**b**) polycentric urban structure of Shanghai; (**c**) morphological parcels and base spatial units used for analysis.

All spatial datasets used for mapping and spatial analysis were first verified and harmonized in WGS 84 geographic coordinates (EPSG:4326). To support metric spatial operations, the datasets were subsequently projected to WGS 84 / UTM zone 51N (EPSG:32651), which was used for Figures 2 and 3 as well as for all distance-, area-, and buffer-based calculations.

Because this study aims to capture fine-scale spatial heterogeneity, we use morphological parcels as the basic units of analysis. Morphological parcels are more appropriate than census blocks because the research object is the functional geography of innovation activities and built-environment morphology, rather than residential enumeration. In Shanghai, census-block-like data are not consistently available as open and fine-grained spatial units, whereas street-network-derived parcels preserve physical barriers created by roads, rivers, campuses, and large development parcels, and correspond more closely to planning intervention units. We acknowledge that the modifiable areal unit problem remains relevant, and future studies could further compare results based on parcels, grids, and administrative units. As Figure 2c shows, the parcel-based approach can adapt to different urban fabrics.

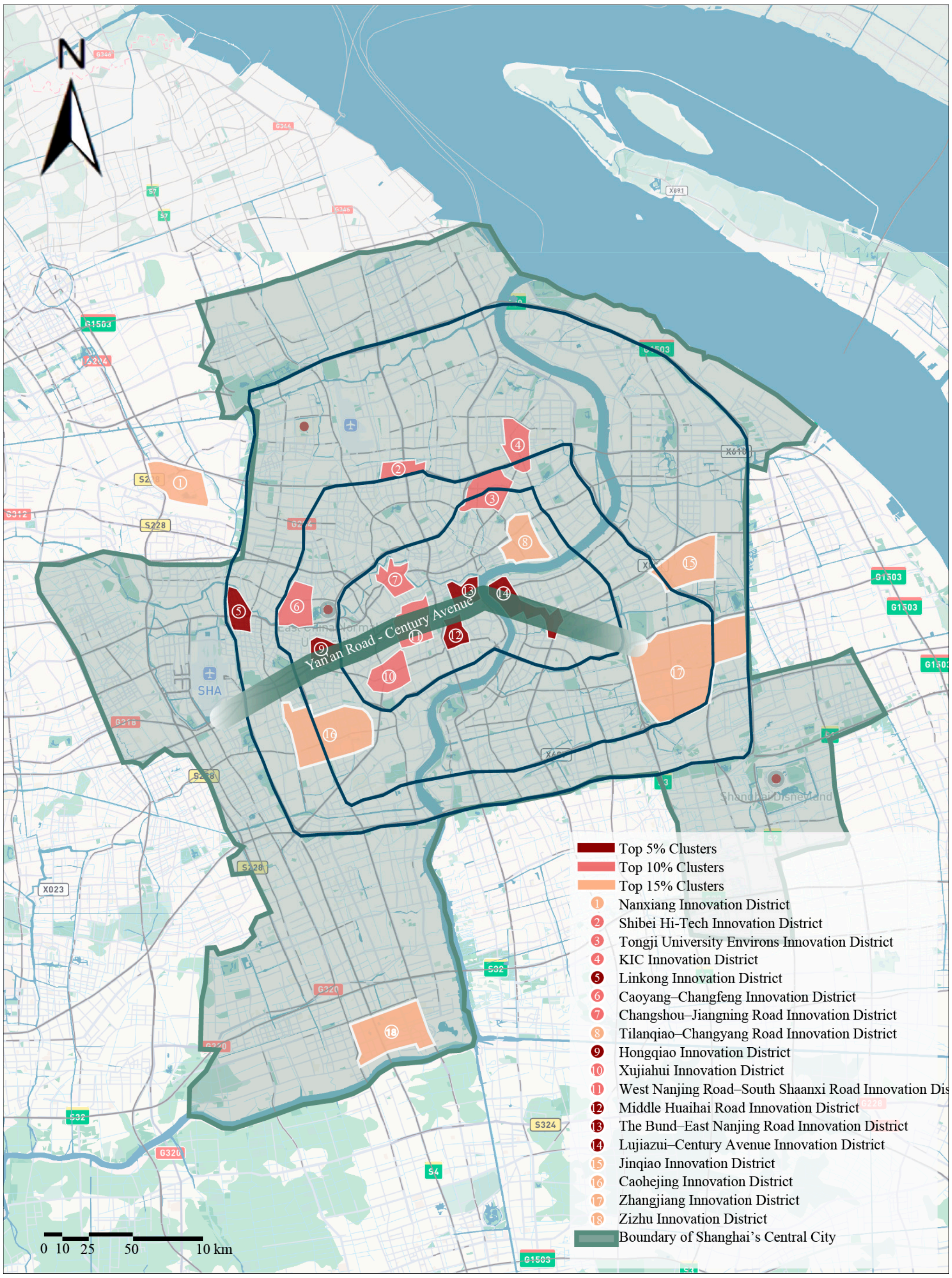

Figure 3. Spatial distribution of urban innovation districts in Shanghai.

3.2. Data Collection and Integration

The first step of this study was to construct a parcel-level geospatial database that captures the multidimensional attributes of innovation districts in Shanghai. The database integrates socio-economic indicators of innovation activity with built-environment indicators describing urban morphology, land-use function, accessibility, and street-level visual quality. As summarized in Table 1, data preparation involved data acquisition, cleaning, geocoding, coordinate transformation, spatial harmonization, and aggregation to the morphological parcel level. Spatial preprocessing, coordinate transformation, point-in-polygon overlay, buffer analysis, and map production were conducted in ArcGIS Pro (v3.2, Esri, Redlands, CA, USA).

Table 1. Category, data type, indicators, source and year.

Category	Data Type	Description/Indicators	Source	Year
Innovation Data	Point	High-tech Enterprises: 27,693 records (e.g., IT, Bio-tech)	Municipal Enterprise Registry	2022
	Point	Innovation Assets: Universities (210), Labs (153), Incubators (198)	Gaode Maps (AMAP); Municipal S&T Commission	2022
	Point	Patent Data: Granted Invention patents	CNIPA	1985–2022
Built Environment	Vector (Polygon)	Building: Building height and floor area Footprints: Attributes include	OpenStreetMap; Cadastral Records	2022
	Vector (Line)	Road Networks: Hierarchy includes expressways, arterial, and secondary roads	OpenStreetMap (OSM)	2022
	Point	Point of Interest (POI): Dining, Shopping, Medical Services, etc.	Gaode Maps (AMAP)	2022
Micro-Environment	Image	Street View Imagery (SVI): 360-degree panoramic images	Baidu; Tencent Maps API	2022

Note: AMAP POI: Points of Interest data from Amap/Gaode Maps, https://lbs.amap.com/ (accessed on 20 June 2026); OSM: OpenStreetMap, https://www.openstreetmap.org/ (accessed on 20 June 2026); Baidu Maps Open Platform: https://lbsyun.baidu.com/ (accessed on 20 June 2026); Tencent Location Service: https://lbs.qq.com/ (accessed on 20 June 2026); CNIPA: China National Intellectual Property Administration; S&T Commission: Science and Technology Commission.

Innovation-activity data were compiled from three main sources. First, a municipal enterprise census was used to identify high-technology enterprises, research and development firms, and producer-service enterprises. Enterprise sectors were standardized according to the national industrial classification standard, GB/T 4754, and enterprises registered after 2022 were excluded to maintain temporal consistency with the study period. Second, a spatial inventory of innovation facilities, including incubators, university laboratories, science parks, and related facilities, was collected to represent the institutional and infrastructural support system for innovation. Third, invention patent authorization records issued by the China National Intellectual Property Administration from 1985 to 2022 were incorporated to capture cumulative innovation output. Patent records were geocoded using the registered address of the applicant or assignee. Records with incomplete addresses, insufficient geocoding precision, or locations outside Shanghai were removed. For patents with multiple applicants, the first Shanghai-based applicant address was retained as the representative location to avoid duplicate counting. The resulting patent points were assigned to morphological parcels using a point-in-polygon procedure. Together, these datasets provide a spatially explicit representation of the distribution and intensity of innovation activity.

Built-environment data were incorporated to describe the morphological and functional characteristics of the urban environment. Parcel-scale and network-scale datasets included points of interest for urban amenities, building footprints, building-height information derived from OpenStreetMap where available, cadastral data, and a complete road-network dataset for accessibility analysis. To capture micro-scale environmental qualities, street-view images were collected from Baidu and Tencent street-view platforms and processed using semantic segmentation to derive visual indicators such as enclosure, visible greenery, and imageability. These data complement conventional geospatial datasets by representing the pedestrian-level visual environment of each parcel.

All datasets were standardized and spatially harmonized before integration. Spatial data were first checked in WGS 1984 for positional consistency and then transformed into a projected coordinate system suitable for Shanghai-based distance, area, and buffer analysis. Positional errors, duplicate records, and redundant points were removed. Enterprise, patent, and point-of-interest records were cleaned and standardized before spatial assignment. To ensure temporal consistency across datasets, observations outside the defined study period were excluded.

Ultimately, all variables were aggregated to 6,105 morphological parcels, which served as the minimum spatial unit for subsequent analysis. Point-based indicators, including enterprises, patents, and points of interest, were aggregated to parcels using point-in-polygon overlay. Road-network indicators were calculated through spatial overlay between parcels and road segments. Building attributes were assigned to parcels through area-weighted aggregation based on footprint coverage. Street-view-derived indicators were linked to parcels using a frontage-buffer matching procedure. The resulting parcel-level dataset provides a homogeneous, fine-grained, and spatially consistent basis for the subsequent classification and analysis of innovation districts.

3.3. Innovation District Identification Framework

Given that Urban Innovation Districts are captured by their actual spatial form rather than administrative boundaries, in this analysis, we develop an approach that explicitly incorporates indicators of innovation activity as well as density-based spatial clustering methods. The approach combines an index-based representation of innovation enabling elements with spatial analysis in order to capture concentration of innovation at a fine level of spatial scale.

For policy use, the HDBSCAN-derived boundary is treated as a functional diagnostic layer rather than a statutory redline. The clustered parcels are used to identify core innovation agglomerations, while adjacent high-score parcels are interpreted as transition areas requiring planning verification. This means that the method first informs where innovation-related land-use coordination, service upgrading, infrastructure investment, and institutional coordination should be considered; the final legal boundary for implementation should then be adjusted through statutory planning procedures, land-parcel ownership review, field inspection, and consultation with district authorities.

3.3.1. Construction of the Innovation Asset Index

“Identification” is made possible by the construction of an index to capture the multi-dimensional character of urban innovation ecosystems. Based on existing indexes [88–90], the indicator system is categorized into three dimensions reflecting different components of innovation activity, namely: (1) innovation capacity, measured by core stock elements such as R&D institutions and 27,693 high-tech enterprises; (2) innovation services, including incubators, financial service providers and technology transfer service organizations; and (3) innovation environment, symbolized by “third places” like cafes and cultural spaces for informal socializing. All indicators are geo-coded and aggregated to the morphological parcels used as the smallest granularity for analysis.

3.3.2. Weighting and Composite Scoring

To integrate heterogeneous indicators into a single aggregate measure, this study adopted a hybrid weighting procedure combining the Delphi method and the Analytic Hierarchy Process (AHP) (Table 2). Expert consultation was used to establish the relative importance of each dimension and indicator, making the weighting process explicit, transparent, and theoretically interpretable. The resulting weights assign greater importance to indicators associated with the core production function and core interaction function of innovation districts, while still retaining the contribution of supporting environmental and accessibility attributes. The Delphi-AHP weights are therefore treated as an expert-informed parameter setting rather than as statistically optimized parameters. Full benchmarking against alternative weighting schemes is acknowledged as a limitation and is left for future robustness testing. The final Innovation Asset Score for each parcel was calculated through weighted linear aggregation of the standardized indicators, producing a continuous measure of the spatial concentration of innovation-enabling elements.

Table 2. Construction and weighting of the innovation asset index system.

<table>
<tr><th>Dimension</th><th>Indicator</th><th>Count (N)</th><th>Data Source</th><th>Indicator Weight (Wi)</th><th>Dimension Weight (Wd)</th></tr>
<tr><td rowspan="4">Innovation Capacity</td><td>University Science Parks</td><td>210</td><td>AMAP POI (2023)</td><td rowspan="3">0.30</td><td rowspan="4">0.50</td></tr>
<tr><td>Key Laboratories</td><td>153</td><td>STCSM</td></tr>
<tr><td>R&D Centers and Institutes</td><td>324</td><td>STCSM</td></tr>
<tr><td>High-tech Enterprises</td><td>27,693</td><td>Innocom</td><td>0.70</td></tr>
<tr><td rowspan="7">Innovation Services</td><td>Technology Services: International Cooperation Bases</td><td>22</td><td>STCSM</td><td rowspan="2">0.35</td><td rowspan="7">0.35</td></tr>
<tr><td>Technology Services: Advanced Service Firms</td><td>485</td><td>STCSM</td></tr>
<tr><td>Spatial Services: Makerspaces</td><td>146</td><td>STCSM</td><td rowspan="2">0.25</td></tr>
<tr><td>Spatial Services: Incubators</td><td>198</td><td>STCSM</td></tr>
<tr><td>Financial Services</td><td>9534</td><td>AMAP POI (2023)</td><td>0.15</td></tr>
<tr><td>Information Services</td><td>548</td><td>AMAP POI (2023)</td><td>0.10</td></tr>
<tr><td>Business Services</td><td>4892</td><td>AMAP POI (2023)</td><td>0.15</td></tr>
<tr><td rowspan="3">Innovation Environment</td><td>Cafés</td><td>7596</td><td>AMAP POI (2023)</td><td>0.70</td><td rowspan="3">0.15</td></tr>
<tr><td>Exhibition Centers</td><td>693</td><td>AMAP POI (2023)</td><td>0.15</td></tr>
<tr><td>Bookstores</td><td>569</td><td>AMAP POI(2023)</td><td>0.15</td></tr>
</table>

Note: STCSM: Shanghai Science and Technology Commission, https://stcsm.sh.gov.cn/ (accessed on 1 June 2025); Innocom: National High-tech Enterprise Certification Network, http://www.innocom.gov.cn/ (accessed on 1 June 2025); AMAP POI: Points of Interest data from Amap/Gaode Maps, https://lbs.amap.com/ (accessed on 1 June 2025).

3.4. Multidimensional Characterization System

A multidimensional characterization system was designed to summarize the spatial, functional, morphological, and environmental diversity of Urban Innovation Districts in Shanghai. Building on existing research linking innovation performance to urban location, built form, functional composition, and environmental quality, the system provides the basis for subsequent dimensionality reduction and typological analysis. As described in Table 3, the characterization system is structured around four analytical dimensions: location, morphology, function, and environment. Indicators were selected according to three criteria: (1) theoretical relevance to innovation-oriented urban form and function; (2) measurability and replicability using existing multi-source urban data; and (3) suitability for parcel-level comparison and subsequent PCA-HCA. The system contains 31 conceptual indicators, which were operationalized as 38 PCA variables after dummy coding categorical measures. Compared with conventional indicator frameworks in innovation district research, this system further incorporates fine-grained morphological indicators and street-view-image-based environmental indicators, allowing the typological analysis to capture both the macro-scale spatial structure and micro-scale urban experience.

Table 3. Multidimensional indicator system of innovation district characterization.

Dimension	Indicator	Unit	Description
Location	Ring-level location	Dummy variable	Relative position of the parcel within Shanghai's ring-road structure (Inner Ring, Middle Ring, Outer Ring, and beyond).
	Metro coverage ratio	%	Share of parcel area located within 800 m of a metro station.
	Mean building coverage	m^2/m^2	Ratio of building footprint area to parcel area.
Morphology	Proportion of super high-rise buildings	%	Share of buildings >100 m within parcel.
	Proportion of high-rise buildings	%	Share of buildings between 30 and 100 m.
	Proportion of mid-rise buildings	%	Share of buildings between 10 and 30 m.
	Proportion of low-rise buildings	%	Share of buildings <10 m.
	Mean building rectangularity	score	Average compactness of all building footprints (1 = highly rectangular).
	Building distribution uniformity	score	Spatial dispersion index of building footprints (1 = uniform, <1 indicates clustering).
	Road network density	km/km^2	Total road length per km^2 of parcel area.
	Intersection density	km/km^2	Number of intersections per km^2.
Function	Share of knowledge-intensive land	%	Share of land used for science, education, and innovation in parcel area.
	Technology-driven enterprise density	enterprises/km^2	Density of high-tech and innovation-related firms.
	SME ratio	%	Share of small and medium-sized enterprises.
	Information technology services density	enterprises/km^2	Density of IT, software, and information service firms.
	Technology promotion and application services	enterprises/km^2	Density of tech-transfer and R&D service firms.
	Professional technical services density	enterprises/km^2	Density of consulting, design, legal, or engineering firms.
	Patent density	patents/km^2	Number of authorized patents within the parcel.
	Education facility density	facilities/km^2	Schools, training institutions (POI-based).
	Healthcare facility density	facilities/km^2	Hospitals, clinics (POI-based).
	Transport facility density	facilities/km^2	Metro entrances, bus hubs, etc.
	Food and beverage facility density	facilities/km^2	Restaurants, cafés (POI-based).
	Culture and recreation facility density	facilities/km^2	Museums, galleries, cinemas, libraries (POI-based).
	Residential land share	%	Share of residential land.
	Historic conservation district share	%	Share of designated heritage-protection areas.

Table 3. *Cont.*

Dimension	Indicator	Unit	Description
Environment	POI diversity (Shannon entropy)	score	Degree of functional diversity using entropy index.
	Green space ratio	%	Share of green/open space area.
	Water area ratio	%	Share of water bodies.
	Street enclosure	score	Street enclosure derived from SVI semantic segmentation.
	Human-scale dimension	score	Height–width ratio of street sections extracted from SVI.
	Visual complexity	score	Texture and element richness detected via SVI segmentation.

Street-view imagery is semantically segmented to create micro-scale environmental measures. These measures quantify enclosure, human scale, visual complexity and imageability, and complement conventional GIS indicators by representing street-level perceptual attributes related to pedestrian activity and casual interaction. Because the study uses existing Baidu street-view imagery and a pretrained semantic-segmentation workflow rather than a newly annotated image dataset, we do not report a newly calculated mIoU, Precision or Recall value. Instead, image-level quality control was applied before aggregation: unavailable panoramas, duplicate images, non-street scenes, severely blurred or occluded images, and observations with invalid coordinates were removed; the remaining indicators were aggregated to parcels to reduce single-image noise. Supplementary Table S6 summarizes these cleaning and reliability checks, and the absence of a manually annotated validation set is acknowledged as a limitation.

3.5. *Typological Classification Strategy*

Following our empirical grounding in studying spatial logics and internal heterogeneities of the innovation districts in Shanghai, we identify a typological strategy by using principal component analysis (PCA) to simplify different dimensions and perform hierarchic cluster analysis (HCA) for data clustering. In that way, complex and high dimensional information is translated into a structure typology that helps for interpretation and planning oriented analysis. The HDBSCAN clustering, principal component analysis (PCA), hierarchical cluster analysis (HCA), cluster-quality metrics, and statistical tests were implemented in Python (v3.10.12; Python Software Foundation, Wilmington, DE, USA), using hdbscan (v0.8.33), scikit-learn (v1.3.2), SciPy (v1.11.4), NumPy (v1.26.4), and pandas (v2.1.4).

3.5.1. Dimensionality Reduction (PCA)

The spatial, functional and environmental indicators are highly correlated, and several conceptual indicators are represented by multiple dummy-coded operational variables. PCA is therefore used as an exploratory dimensionality-reduction step to summarize dominant patterns while reducing redundancy before typological clustering. The 31 conceptual indicators were operationalized as 38 PCA variables, and min–max normalization was applied before PCA so that variables measured on different scales could be compared on a common bounded scale.

$$Z_{ik} = \sum_{j=1}^{p} w_{jk} X_{ij} \quad (1)$$

where X(i,j) is the standardized value of indicator j for innovation district i; w(j,k) is the loading of indicator j on principal component k; Z(i,k) is the score of innovation district i on principal component k; p is the total number of indicators; k indexes the retained principal components.

Component selection is informed by the Kaiser criterion, the scree plot and the cumulative proportion of explained variance. For the final 18 UIDs, the first six principal components explain 81.59% of the total variance (Supplementary Table S1). The complete unrotated component coefficient matrix and the Varimax-rotated coefficient matrix are reported in Supplementary Tables S4a,b and S5a,b to improve interpretability. Component labels are used only as empirical summaries of high-loading variables; they should not be interpreted as deterministic theoretical categories or causal mechanisms.

3.5.2. Clustering Procedure (HCA)

Scores of the retained principal components were used as the input for typological classification. This step avoids applying HCA directly to the full 38-variable matrix, where correlated density, amenity, and dummy-coded variables could have an excessive influence on groups of similar indicators. Hierarchical Cluster Analysis (HCA) was then conducted using Ward's linkage method and Euclidean distance to identify groups of parcels with similar multivariate profiles. Ward's method was selected because it minimizes the increase in within-cluster variance at each merging step and tends to produce compact and interpretable groups suitable for spatial and morphological classification. The Ward linkage between two clusters (A) and (B) is defined as follows:

$$\Delta(A,B) = \frac{|A||B|}{|A|+|B|}\|\mu_A - \mu_B\|^2 \tag{2}$$

Note:
∣A∣ and ∣B∣ denote the number of innovation districts in clusters A and B;
μA and μB are the centroid vectors of clusters A and B in the principal component space;
‖·‖ denotes the Euclidean distance.

To reduce arbitrariness in selecting the number of types, candidate HCA solutions from k = 2 to k = 8 were evaluated using the silhouette coefficient, Davies–Bouldin index, Calinski–Harabasz index, within-cluster sum of squares and cluster-size balance (Supplementary Table S2). The five-cluster solution is not claimed to be statistically optimal under every metric. To further make the planning interpretation transparent, we added a radar-profile comparison for k = 3, k = 4, k = 5 and k = 6 and summarized the planning interpretability of these alternatives in Supplementary Table S7. The k = 3 and k = 4 solutions merge several policy-relevant profiles, especially academic knowledge districts and central business/headquarters districts, whereas k = 6 begins to split a small profile without adding a clearly actionable planning category. The k = 5 solution is therefore retained as a balanced classification that preserves planning-relevant distinctions while avoiding excessive fragmentation.

4. Results

4.1. Data-Driven Identification of Urban Innovation Clusters

The clustering results reveal spatial concentration in innovation activities at different spatial scales in the whole metropolitan Shanghai. There are 18 significant innovation clusters identified altogether (Table 4), only accounting for 1.56% of the municipality land but composing a large share of registered innovation-related activities in the city. Such strong spatial concentration suggests a high selectivity of innovation activities to urban space in this city. The HDBSCAN settings were not treated as universal default values; they were selected through exploratory calibration to Shanghai's dense parcel structure, expected district scale and spatial continuity, and then checked against moderate density-connectivity perturbations (Supplementary Table S3). The baseline output contains 454 clustered parcels from 6,105 candidate parcels, forming 40 algorithmic micro-clusters before contiguity-based synthesis into the reported UID areas. Under three moderate perturbation settings, high-value core-parcel retention ranges from 87.22% to 92.95%, while full-boundary Jaccard overlap remains lower (0.206–0.216). This suggests that the core agglomerations are relatively stable, but peripheral parcels are sensitive; the detected UID boundaries are therefore interpreted as fuzzy functional edges rather than fixed administrative lines.

Table 4. Basic information on innovation districts in Shanghai.

Parcel ID	Innovation District Designation	Area (km^2)	Total Innovation Assets	Innovation Asset Density
1	Nanxiang Innovation District	5.811	0.229	0.039
2	Shibei Hi-Tech Innovation District	2.190	0.306	0.140
3	Tongji University Environs Innovation District	4.266	0.783	0.184
4	KIC Innovation District	3.557	0.577	0.162
5	Linkong Innovation District	2.272	0.855	0.376
6	Caoyang–Changfeng Innovation District	3.786	0.521	0.138
7	Changshou–Jiangning Road Innovation District	2.307	0.335	0.145
8	Tilanqiao–Changyang Road Innovation District	4.354	0.53	0.122
9	Hongqiao Innovation District	1.980	1.011	0.511
10	Xujiahui Innovation District	3.340	0.498	0.149
11	West Nanjing Road–South Shaanxi Road Innovation District	4.060	1.512	0.372
12	Middle Huaihai Road Innovation District	1.916	1.235	0.645
13	The Bund–East Nanjing Road Innovation District	1.986	1.453	0.732
14	Lujiazui–Century Avenue Innovation District	4.445	1.877	0.422
15	Jinqiao Innovation District	6.785	0.502	0.074
16	Caohejing Innovation District	12.375	1.706	0.138
17	Zhangjiang Innovation District	24.082	1.604	0.067
18	Zizhu Innovation District	9.413	1.205	0.128

As we can see from Figure 3, these identified clusters compose a dense inner core, then several kinds of secondary nodes are distributed around the core. The densest corridor extends from the Bund to Nanjing Road and Lujiazui to Zhangjiang, constituting the main spine of innovation intensity in the urban metropolitan area. Clusters located in Nanjing West Road, Huaihai Road, around the Bund area and along the corridor of Lujiazui and Century Avenue are the densest ones, all above 0.35 to 0.70 innovation assets per hectare density level. These places correspond to places with high transport accessibility, as well as the concentration of the finance, digital services and design oriented industries. Similar inner-core dominance has been documented for London's Knowledge Quarter [91] and Tokyo's Shibuya innovation district [92].

Such a pattern is consistent with our previous work showing that knowledge intensive activities of Chinese megacities remain skewed towards central urban areas although the urban sprawl in China continues in the suburbs [93]. A distinct west dense and east sparse gradient exists. Fifteen out of eighteen clusters are located in Puxi while only three are located in Pudong. Such an imbalance reflects long-standing differentials in resources of higher education, land markets and infrastructure investments on both sides of the Huangpu River. Despite large policy orientation to promote development eastwards, the continuing dominance of innovation to the historic urban core region points to strong spatial path dependency. Such phenomena also exist in Seoul, where legacy universities and research centers anchor innovation activities to central districts.

At the metropolitan periphery, some clusters (e.g., Nanxiang cluster and Zizhu Science Park) have low density levels but have larger fields. Both characteristics suggest an early stage of spatial diffusion and an out-pushing of innovation-related functions around it at a relatively low level. Such a pattern has also been found in the Yangtze River Delta region [94]. Such a pattern is similar to findings in the Yangtze River Delta: that peripheral innovation areas originate with established cores, not to replace them.

That spatial pattern revealed by clustering was in close agreement with the strategic structure described in Shanghai's Fourteenth Five Year Service Industry Plan. The overlay between data underlying innovation agglomerates and policy inspired spatial areas indicated that the market-driven location behavior becomes more in line with spatial governance behavior. The innovation districts are not merely the by-product of zoning interventions. Innovation districts emerged along space trajectories formed by economic processes and planning, and the process of policy and market co-evolution found also in complex urban policy phenomena [95].

Analysis of cluster morphology and functional composition shows three large categories of urban spatial types. Compact inner core clusters are high-density clusters, vertical land use and service-oriented specialization. University-anchored knowledge districts feature universities alongside adjacent innovation activities. Peripheral integrated parks combine research features with production-oriented uses at larger spatial scales. These spatial types indicate a development away from traditional models of science parks to a broader range of distinctively multi-centered innovation configurations. Similar changes have been observed in various international cases, such as the 22@ district in Barcelona and the Seaport District in Boston [96].

4.2. Multi-Evidence Validation and Policy Relevance

Finally, to assess the empirical plausibility and policy relevance of the delineated innovation clusters, we apply a multi-evidence comparison that combines patent-density patterns and institutional matching analysis. Because patent density is also used in the multidimensional characterization stage, the patent comparison is interpreted as supporting evidence for the delineated innovation geography and as one part of a convergent evidence check, rather than as standalone typological validation.

4.2.1. Patent-Based Validation

Patent data are used here as an indicator of the spatial distribution of innovation registration rather than as an exact measure of the physical site of R&D or production. The highest concentrations are in Zhangjiang, Caohejing and Lujiazui, areas that correspond to high-density innovation nodes observed from spatial clustering. A few patent concentrations, such as Luodian and Gaoqiao, appear outside the identified clusters, which may represent emerging or sector-specific registration activity that has not yet reached cluster scale.

Comparison between clustered and non-clustered areas is therefore used as a convergent evidence check (Figure 4). Patent registration density is higher in the identified innovation districts than elsewhere in the city, and a Mann–Whitney U test indicates that this difference is statistically significant at the 0.0001 level [97]. However, because patent data partly overlap with the characterization indicators and represent registered applicant or assignee locations rather than exact sites of invention, the patent comparison should be read as supporting evidence for the delineated geography of innovation registration rather than as a standalone validation of physical innovation production or typological classification.

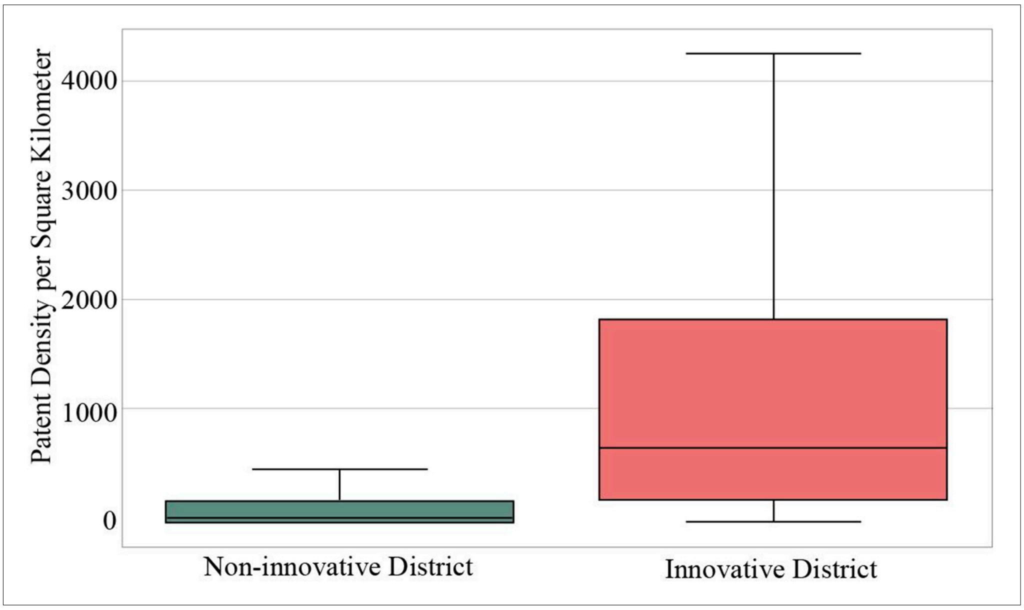

Figure 4. Comparison of patent density between identified innovation districts and non-district areas in Shanghai (boxplots).

4.2.2. Alignment with Policy and Institutions

Table 5 shows the institutional relevance in comparing with municipal innovation-related policy designations. We review 18 policy documents and identify the innovation carrier and strategic development area designated by the official policy. Most innovation-oriented policy emphasis areas are within the area of our identified innovation clusters, especially in those places such as Zhangjiang, Caohejing and several university-anchored districts, etc. This overlap gives an indication that the clusters reflect not just the market-driven agglomeration but also spatial emphasis in Shanghai's innovation-related policies and governance.

At the same time, some policy designated areas such as Lingang, West Bund AI, and G60 Corridor also are not detected through data driven clustering. These areas are relatively new developments where the innovation-related factors have not accumulated to a measurable extent. As contrast, some mature and dense innovation areas, such as Caoyang and Changfeng, are discernible in the clustering results, but are not present in policy documents today. Such locations represent market led innovation centers that emerge ahead of policy designation. The observed discrepancy reflects a dual formation mechanism. In some places, planning processes precede the formation of innovation aggregation; in others, innovation aggregation emerges first, followed by policy designation. The duality points out the significance of adaptive land use and innovation planning so as to accommodate emerging innovation geographies and support long term strategic corridors.

Table 5. Policy-designated priority areas used for policy-alignment comparison and institutional relevance assessment of detected UIDs in Shanghai.

Policy Document Title	Policy Priority Areas
Shanghai Municipal 14th Five-Year Plan for Building a Science and Technology Innovation Center with Global Influence	Zhangjiang Science City; Zhangjiang National Independent Innovation Demonstration Zone; Lingang New Area; Yangtze River Delta G60 Science and Technology Innovation Corridor; Science and Technology Innovation Hubs in Minhang, Yangpu, Xuhui, Jiading, Songjiang, and other districts; University Science Parks (such as the Tongji Knowledge Economy Circle and Zero Bay Innovation and Entrepreneurship Cluster)

Table 5. *Cont.*

Policy Document Title	Policy Priority Areas
the 14th Five-Year Plan for the Service Industry in Shanghai (2021–2025)	Core and Radiation Zones: Central Activity Zone (CAZ), Service Industry Vitality Belt along both banks of the Huangpu River, Service Industry Innovation and Development Belt along the Yan'an Road-Century Avenue axis.
Shanghai Urban Renewal Action Plan (2023–2025)	Strategic Growth Poles: Lingang New Area, Yangtze River Delta Ecological Green Integrated Development Demonstration Zone, Hongqiao International Open Hub.
Shanghai's 14th Five-Year Plan for Artificial Intelligence Industry Development	New Towns and Specialized Demonstration Zones: Jiading New Town, Qingpu New Town, Songjiang New Town, Fengxian New Town, Nanhui New Town; Zhangjiang Science City, North Bund, Jing'an National Comprehensive Pilot Zone for Service Industry Reform, Changning Airport Economic Demonstration Zone, etc.
Shanghai Zhangjiang Science City Development Plan for the 14th Five-Year Period	Other Key Areas: Xicun Science and Innovation Center, Caojing Industrial Internet Industrial Base, Qingpu National Logistics Hub, etc.

4.3. Key Influencing Factors of Spatial Pattern Formation

Based on the multivariate analyses described above, the spatial characteristics of innovation districts in Shanghai can be summarized through several empirical dimensions linking centrality, industrial composition, spatial configuration and environmental conditions. PCA provides a compact representation of this structure (Figure 5): the first six principal components explain 81.59% of the total variance, which supports their use as an exploratory basis for subsequent typological analysis.

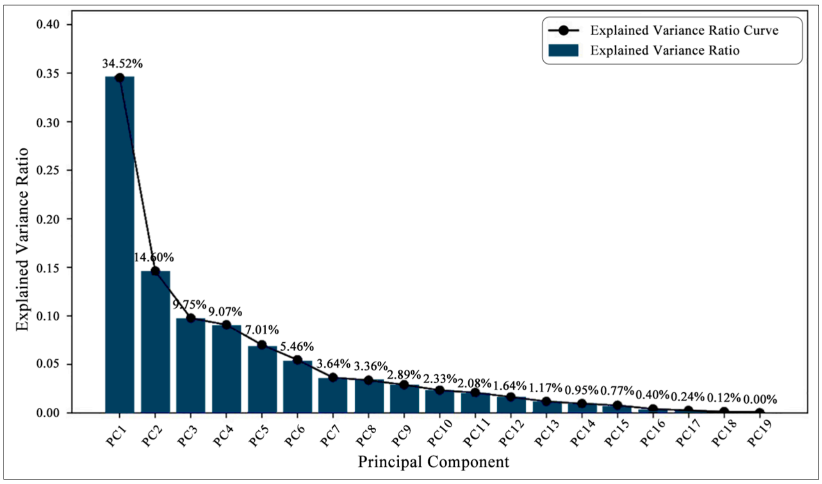

Figure 5. Scree plot of explained variance ratios for principal components.

The loading heatmap (Figure 6), together with the complete unrotated and Varimax-rotated coefficient matrices in Supplementary Tables S4a,b and S5a,b, shows how variables group across the retained components. These groupings are used to assign cautious empirical labels to the components. The labels summarize dominant variable associations and should not be treated as deterministic causal explanations of innovation geography.

Figure 7 shows the position of the eighteen innovation districts along the first two principal components (PC1 and PC2). PC1 is interpreted as an amenity and centrality gradient because it is associated with transport accessibility, shopping, cultural, education and health services. High-scoring areas such as the Bund-East Nanjing Road and Middle

Huaihai Road are dense and mixed-use urban centers where agglomeration economies and knowledge spillovers are likely to be strong. This pattern is consistent with international evidence that centrally located and amenity-rich districts often remain important sites of innovation activity.

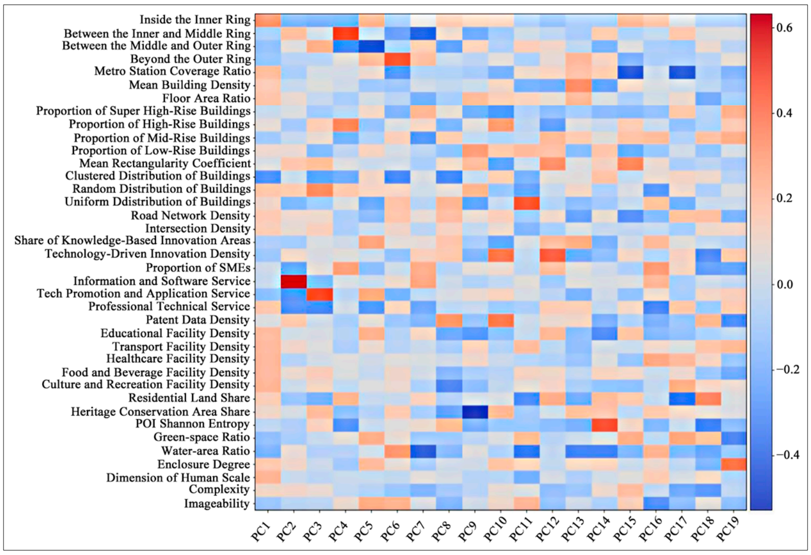

Figure 6. Heatmap of variable loadings on principal components.

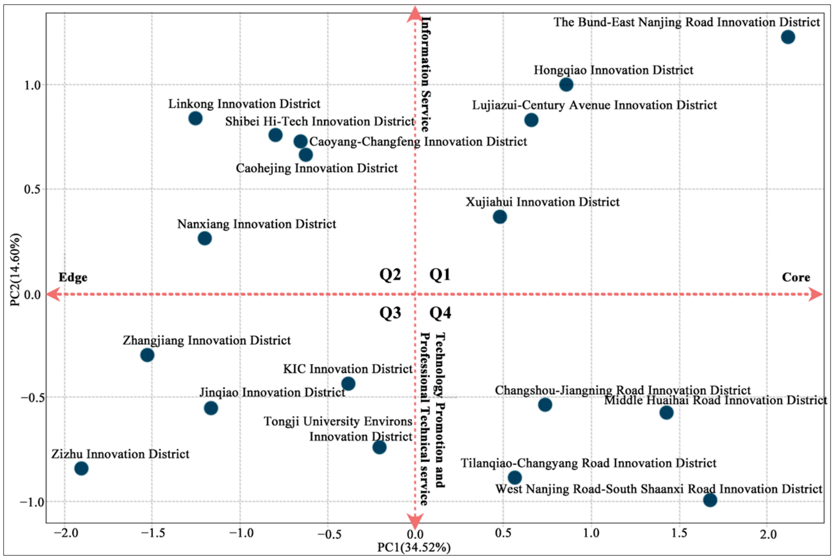

Figure 7. PCA score plot of urban innovation districts along the first two principal components.

PC2 differentiates districts with stronger information services, software activities and finance-oriented knowledge sectors from districts with stronger research-institute, professional-technical-service and SME-related profiles. When the 18 innovation districts are represented along PC1 and PC2, their positions suggest a contrast between central digital-service hubs and more science- or research-oriented districts. This contrast is interpreted as an empirical pattern rather than as a fixed typological boundary.

PC3 is interpreted as a historic-form and creative-activity dimension because high-scoring districts tend to combine fine-grained street networks, adaptive built fabric, and creative or professional service activities. Inner-city districts such as the Middle Huaihai Road area and the Bund illustrate how entrepreneurship and creative milieus can coexist with historically layered urban form [98].

PC4 is interpreted as a middle-ring development-density dimension, illustrated by districts such as Hongqiao and Caohejing. These areas combine relatively high building density, active SME development, and mixed residential-commercial uses, resembling former industrial or business-park areas that have become more urbanized over time [99].

PC5 is interpreted as a knowledge-anchor and environmental-quality dimension, as districts such as Tongji, Zizhu, and Zhangjiang combine research institutions with greener or more spacious urban settings. PC6 is interpreted more cautiously as a peripheral or waterfront landscape dimension. Although PC6 explains a smaller share of variance, it helps distinguish districts such as Nanxiang and Zizhu from more compact central districts by capturing the role of waterfront access, open landscapes, and peri-urban spatial resources.

Hierarchical cluster analysis (Figure 8) assigned the eighteen innovation districts into five internally coherent types, each defined by a different combination of the six principal components. The five-type solution was retained as a balanced and interpretable classification after comparing candidate (k = 2) to (k = 8) solutions using cluster-quality metrics and cluster-size balance. The resulting types are: peripheral information-technology-oriented industrial parks; university-led research and incubation clusters; central high-density business and digital-service districts; global-facing finance and headquarters districts; and historic mixed-use areas with creative and professional services.

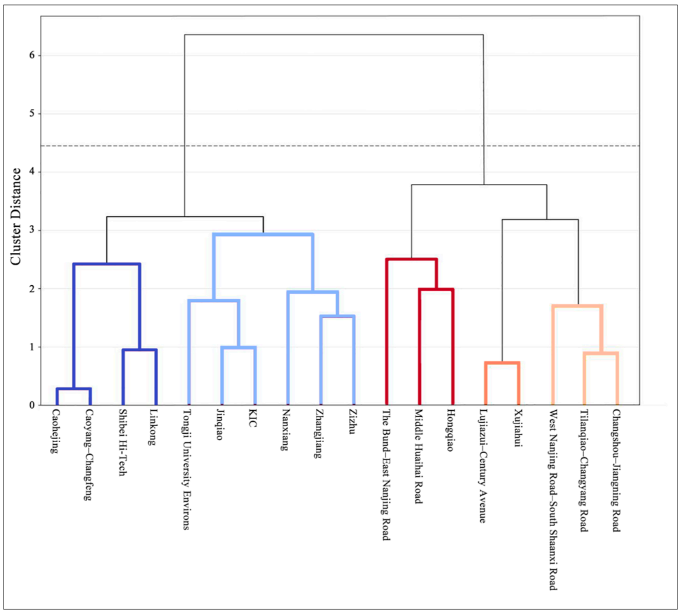

Figure 8. Hierarchical clustering dendrogram of urban innovation districts based on principal component scores. **Note:** The same color represents the same cluster.

The dendrogram is interpreted together with the k = 2–8 cluster-quality diagnostics in Supplementary Table S2. Although k = 7 and k = 8 produce slightly higher silhouette values and lower Davies-Bouldin values, they generate singleton clusters and fragmented categories that are less useful for planning interpretation. Therefore, the five-type solution is retained as a balanced classification. The comparative radar profiles for k = 3, k = 4, k = 5 and k = 6 (Figure 9) further show that k = 5 provides a clearer balance between profile differentiation and planning interpretability. The district-level radar profiles (Figure 10) show that each district combines the six underlying empirical dimensions in distinctive ways.

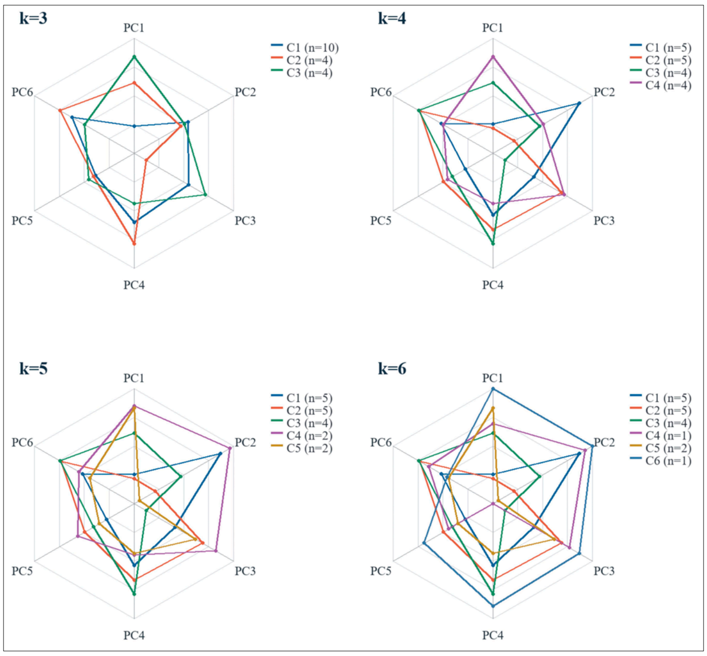

Figure 9. Radar-profile comparison of alternative HCA solutions for k = 3, k = 4, k = 5 and k = 6 based on mean principal-component scores.

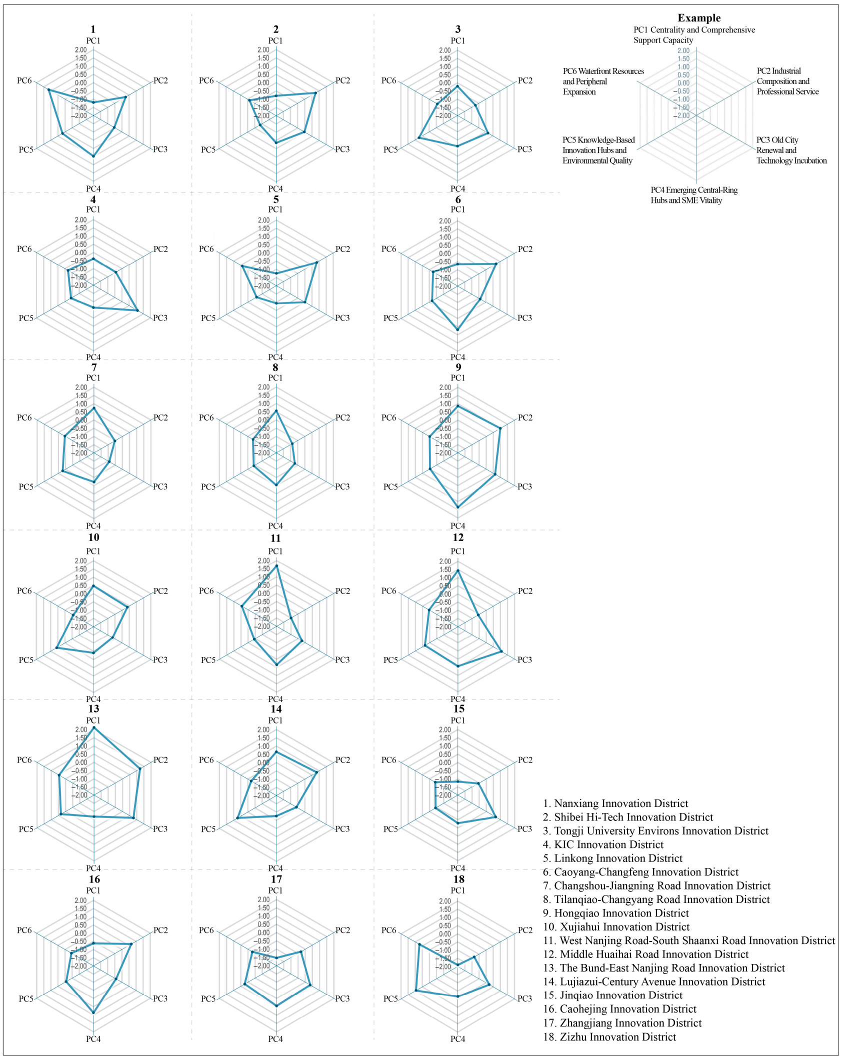

Figure 10. Radar plots of principal component scores for identified urban innovation districts in Shanghai.

5. Discussion

5.1. Typology and Planning Implications of Innovation Districts

An integrated spatial typology of innovation districts in Shanghai is proposed based on the PCA–HCA classification results as well as observed morphological and functional properties of the underlying urban fabric (Figure 11). The typology of innovation districts views innovation districts not as types but instead, as a gradient of configurations formed by intensity of land uses, entity anchorage, industrial specialization and urban integration levels. Five types are identified, including peripheral specialized innovation city zone, academic knowledge innovation city zone, core integrated business and industry zone, global capital and headquarters zone, creative renewal and fusion city zone, etc. These types are multi scalar rather than form isolated ones, representing differentiated patterns of innovation within a polycentric metropolitan system formed by public policies.

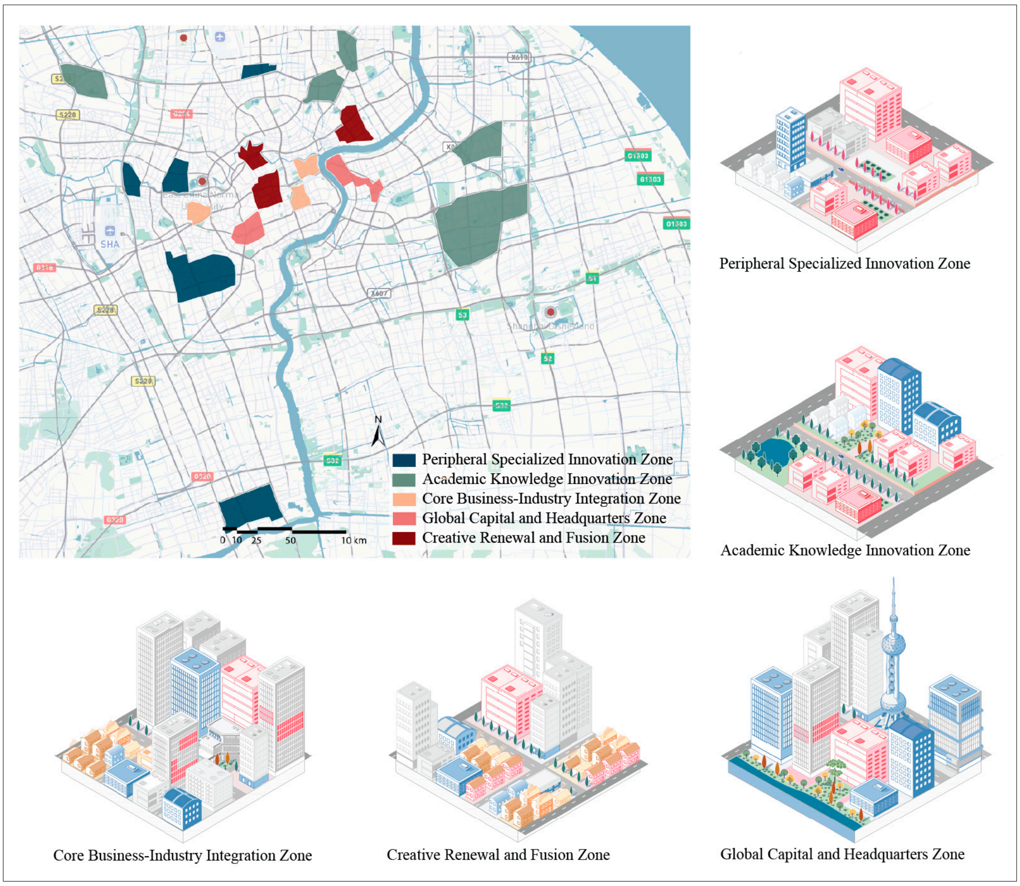

Figure 11. Spatial distribution and schematic representations of five typologies of urban innovation districts in Shanghai.

From a spatial structural perspective, the 5 types overall capture an inner to outer ring pattern of the spatial pattern of innovation development. High density and amenity rich districts are clustered in the inner urban area, and much larger, more specialized innovation areas come to emerge around the metropolitan periphery. This order corresponds to differences in building densities, services, dominant industry contents and environmental quality among district types. Our typology reveals that innovation development in high density Chinese cities evolves in a hybrid spatial pattern, influenced by both market-driven agglomeration and state-led spatial coordinated formation processes, rather than by a transformation from suburban science parks towards the core urban districts.

Overviews in the peripheral specialized innovation zones demonstrate this hybrid logic. These zones represent medium density research and development clusters organized around larger block structures and encased in automobile-oriented cities with low amounts of functional mixing. The innovation activity within these zones is strongly concentrated in, for example, digital technology or manufacturing-related industries, and urban amenities are relatively poor. Such spatial patterns align with results of the PCA, where scores were relatively low on centrality and amenity-based components and high on component scores for industrial concentration. This character of the evolving pattern prioritizes land supply and scalability above urban integration, which suggests that future spatial strategies should focus on increasing land use diversity, improving the supply of public spaces and facilitating the natural evolution from an industrial spine towards fuller urban neighborhoods.

In contrast with the moderate difference amongst academic knowledge innovation zones, these types of areas display a very different landscape layout. Their characteristic landscape appearance includes porous campus boundaries, smaller campus blocks, a higher share of green areas, and distributed centers of innovation (such as incubators or university-affiliated laboratories), relatively low commercial intensity (as reflected by lower scores on PC1) and prominent knowledge-intensive activities (as reflected by the scores of PC3 and PC5 being relatively high). These features accentuate the anchoring role of universities in the creation of local knowledge spill-overs. The landscape patterns imply that policies for academic knowledge innovation zones need to prioritize the reinforcement of the links between campuses and surrounding urbanity, protecting the affordable land for research services, and using zoning instruments to permit variable R&D uses but preclude land speculation.

Within the urban core, core business and industry integration zones and global capital and headquarters zones are located in zones providing the highest degree of amenity. These zones are concentrated in dense mixed-use urban forms and are also amongst the areas that most strongly feature advanced services activities, which also generate high values in PC1. Core business and industry integration zones combine high-rise office development with commercial and cultural activities, resulting in a type of hybrid innovation environment with leading information services and headquarters firms from emerging enterprises. Global capital and headquarters zones, exemplified by districts such as Lujiazui, stand out with intense verticalization, iconic architecture and global financial activity, with principal component values being high for PC1 and PC2 (that is, centrality, information and finance specialization) and high values in PC5 relative to urban image attributes.

These characteristics illustrate how reliant global-oriented innovation activities are on existing agglomeration economies. From a land use perspective, this suggests that there is a need to place a greater focus on fine-grained urban renewal, improvement of transit capacity, and policy interventions that retain mid-range office space to avoid location displacement by innovative SMEs.

Popular creative renewal and fusion zones are usually found in historical industrial or mixed-use districts in renovation. They feature lower to mid-rise block forms, urban fabric with historical character and smaller extent of densification. Such places are conducive to innovation activity in design, arts and professional services, and are consistent with lower PC2 and PC3 scores, capturing contrasts with concentration of information and finance specialization, and formal research intensity. Innovation dynamics in such zones require less reliance on large scale research investment, but rely instead on cultural capital, fine-grained city block street networks and adaptive reuse of buildings. Future strategies for place over time should therefore reinforce the conservation of heritage, create affordable office space for the creative economy and encourage regeneration dynamics from the bottom up.

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Collectively, the five types imply that the innovation-associated spatial development in Shanghai goes through a layer instead of a single path and multiple innovation logics occur simultaneously in Shanghai's metropolitan structure. Innovation districts not only act as economic clusters, but also become an institutional land use pattern, which is negotiated by zoning systems, campus institutional arrangements, state-coordinated development regimes and the planning policy. The typology also indicates the importance of type-specific spatial governance in which land allocation, functional mix and re-development tools are coordinated with different innovation paths. Such an arrangement offers a basis of adaptive and spatialized strategy that support various innovations from research-intensive development to creative industry development and small local ventures.

5.2. Transferability and Limitations

Our previous discussion suggests that innovation districts in Shanghai are formed by interacting conditions for centrality in space, functions and composition, institutional support and innovation capacity. Although the five type classification is from a high density urban context and strong public coordination, the mechanisms identified by our analysis are relevant to the more general debates on metropolitan innovation governance. There are three important lessons for them. The first lesson is that innovation capacity is spatially structured, not homogeneous. Core districts are set apart by the concentration of knowledge-intensive activities, diversified functions, and high connectivity, while the edges of the districts are more specialist and clustered, supported by public policy. This pattern is consistent with existing evidence from other world cities such as Boston, Seoul and Singapore. It suggests that metropolitan innovation policy can and should be distinguished between district types, rather than tried and managed through uniform policies across the entire city.

Second, land use regulation and spatial planning instruments play a major part in influencing outcomes for innovation. Alignment between the identified clusters, patent concentrations and planning policy documents' strategic zones suggests that flexibility of zoning, repositioning of use and strategic land supply impact the capacity of innovation-related functions to cluster spatially. This supports views in recent international scholarly literature that innovation districts are spatial policy instruments, not just platforms for industrial policy. For implementation, fuzzy functional boundaries should therefore be converted into policy redlines through a boundary-solidification mechanism. We propose a four-step translation: first, use the HDBSCAN result to identify the core parcels and transition parcels; second, overlay these parcels with legally recognized planning units, cadastral parcels, road and river barriers, and existing administrative boundaries; third, conduct field verification and stakeholder consultation to confirm whether transition parcels should be included; and fourth, formalize the adjusted boundary through statutory land-use planning, zoning overlays, renewal-unit designation or district-level innovation policy. In this way, fuzzy analytical edges are used to guide evidence-based policy discussion, while final redlines remain compatible with administrative and legal planning practice.

Third, the typology offers guidance to diagnose and strategize beyond the case itself. In cities with existing innovation areas, districts can be classified according to location, industry composition and urban morphology and interventions designed in accordance with local characteristics. Examples include backing for mixed land use transformation in the specialized peripheral districts, strengthening university–industry partnerships in academic districts, among others. Interventions could also be targeted at improving space density, digitized service provision in central districts, upgrading service infrastructures in headquarters-oriented districts, or the balancing act between heritage conservation and creative economy development in new classic renewal districts. For the innovational

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districts in the making, our findings also deliver a set of guiding principles on accessibility, business demands and location, characteristics of spatial form conducive to openness and street-level interactions over enclosed park layouts and space.

Overall, the case evidence suggests that innovation districts are most successful when spatial structure, land use decisions, and institutional structures are well aligned. Governance conditions vary across cities but, from our findings, the mechanisms do provide a transferable basis for metropolitan innovation policy. They include spatial differentiation, land use integration and policy design. Together, they allow for more tailored forms of city policy designed to enhance place-based innovation capacity within the national and international network of innovation. Stronger future validation should incorporate independent firm-growth, employment, investment, talent-flow and longitudinal innovation-output datasets, so that the delineated geography can be evaluated with evidence not used in either delineation or typological characterization.

A further limitation concerns the spatial meaning of patent data. Registered applicant or assignee addresses can differ from actual R&D laboratories, production sites or project teams, especially for headquarters firms, platform companies and multi-site enterprises. We did not apply a citywide enterprise-park correction algorithm because a complete and verifiable database linking every patent to its actual R&D site was unavailable. Therefore, patent figures in this paper should be interpreted as the spatial distribution of innovation registration, not as the absolute physical geography of innovation production. Future work could improve localization by integrating enterprise-park rosters, firm branch addresses, R&D facility databases and manually verified coordinates for major patenting organizations.

The transferability of this study lies primarily in the analytical workflow rather than in the Shanghai-specific thresholds or typological labels. Applying the framework to another city would require comparable parcel-scale data on innovation enterprises, patents, POI, buildings, road networks and street-view-derived environmental attributes. For Latin American metropolitan regions, the workflow may be useful for comparing policy-designated innovation corridors with observed concentrations of firms, universities, services and urban amenities. However, direct transfer should account for higher informality, uneven public-transport access, safety conditions, labor-market segmentation and fragmented governance. Thus, the framework is transferable as an analytical workflow, while thresholds and typological labels should be recalibrated locally.

Although the exploratory stability check supports the relative stability of high-value core parcels, full HDBSCAN parameter sweeps, alternative weight-scheme benchmarks, direct-HCA comparisons and independent cross-city validation remain important extensions for future research.

6. Conclusions

Our paper provided a spatially explicit workflow to pinpoint and describe typology urban innovation districts in a large, multi-centered metropolitan area. Using Shanghai as an example city, we examined the relationships among innovation activities, urban milieu in which they sit, and their spatial patterns with reference to urban morphology and function, accessibility, institutional architecture and environment. Our analysis advanced innovation district research by spatially identifying, multidimensionally describing and typologically classifying urban innovation districts as part of the empirical approach.

Our results showed that innovation activity in a rapidly urbanizing city like Shanghai is not cleanly mapped with administrative or planning boundaries. To adjust for this mismatch, we applied a density-based identification procedure that combines hierarchical thresholding based on head/tail breaks with spatial clustering using HDBSCAN. This procedure identified 18 innovation districts whose boundaries are reflective of observed agglomeration patterns rather than neat planning boundaries. Supplementary stability checks also suggest that high value core parcels are fairly stable under relatively small density-connectivity perturbations, but boundary parcels located in the periphery are quite unstable. Therefore, the identified boundaries should be treated as fuzzy functional boundary edges, rather than fixed administrative boundaries.

The study also developed a multidimensional conceptual characterization system encompassing 31 conceptual indicators, operationalized as 38 PCA variables, describing the location conditions, spatial form, functional content and quality of the environment. Exploratory PCA of these variables condensed them into six PCA components, explaining 81.59% of the total variability. These components represent some of the primary empirical dimensions of urban innovation districts' heterogeneity—i.e., amenity centrality, information service specialization, historic form and creativity, middle ring development density, knowledge anchors and environmental quality and peripheral waterfront features.

On the basis of these components, hierarchical clustering classified the 18 innovation districts into five types. We retained the (k = 5) solution as a balanced and reasonably interpretable classification after evaluating (k = 2) versus (k = 8) solutions by comparing cluster-quality metrics and cluster-size balance. The types reveal that innovation districts in a large Asian metropolitan area can be much more diverse than a single canonical model might suggest. They include peripheral information-technology-oriented industrial parks, university-led innovation research and incubation clusters, central densely developed business and digital-service districts, global-facing finance and headquarters districts, and a historic mixed-use area with creative and professional service businesses. These differentiated types show that innovation districts have type-specific spatial, land-use and governance strategies.

These results have important implications for metropolitan land-use management and innovation-focused planning. Innovation performance is not just related to local industrial specialization or designations by policies, but also to parcel-scale spatial structure and function mix, accessibility, institutional anchors and quality of environmental quality. Innovation planning cannot solely rely on instruments of industrial policy or on land quotas. More effective forms of planning should merge land-use regulation, urban design, urban transport accessibility, public space provision, environmental improvement and type-specific resources of governance instruments. In this sense, the workflow we propose provides a practical setting for evidence-informed planning and space resource efficient use.

For other megacities, one can transfer the framework as a practice workflow, but one would need to adjust the thresholds, indicator weights and label names to a different local data profile, institutional context, urban morphology, etc. Future work should apply the workflow to multiple cities; compare the PCA-HCA strategy with direct HCA on the whole operational indicator matrix and include independent longitudinal data sources on firm growth, employment, investment, flows of talent and innovational outputs. These extensions would help us to understand how innovation districts change over time and how (spatial planning) interventions impact their long-term evolution patterns.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi15070298/s1. Table S1: Explained variance of the retained principal components; Table S2: Cluster-quality metrics for HCA solutions from k = 2 to k = 8; Table S3: Exploratory HDBSCAN core-stability check under moderate density-connectivity perturbations; Table S4: (a) Complete unrotated PCA component coefficient matrix, variables 1–19; (b) Complete unrotated PCA component coefficient matrix, variables 20–38; Table S5: (a) Varimax-rotated PCA component coefficient matrix, variables 1–19; (b) Varimax-rotated PCA component coefficient matrix, variables 20–38; Table S6: Street-view semantic-segmentation data cleaning and reliability checks; Table S7: Planning-interpretability comparison of alternative HCA solutions.

Author Contributions: Conceptualization, Haifeng Diao, Weiyi Jia and Menglin Ding; methodology, Weiyi Jia, Menglin Ding, Ruiqi Chen and Haifeng Diao; software, Weiyi Jia and Haifeng Diao; validation, Menglin Ding, Ruiqi Chen and Weiyi Jia; formal analysis, Menglin Ding; investigation, Haifeng Diao, Weiyi Jia and Menglin Ding; resources, Haifeng Diao and Menglin Ding; data curation, Haifeng Diao and Ruiqi Chen; writing—original draft preparation, Menglin Ding and Ruiqi Chen; writing—review and editing, Ruiqi Chen, Haifeng Diao and Weiyi Jia; visualization, Menglin Ding and Haifeng Diao; supervision, Weiyi Jia; project administration, Weiyi Jia; funding acquisition, Weiyi Jia. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data analyzed in this study were obtained from publicly available and third-party sources, as described in the manuscript.

Acknowledgments: The authors sincerely thank the academic editor and anonymous reviewers for their constructive comments and suggestions, which helped improve the clarity and quality of the manuscript. The authors also gratefully acknowledge the guidance and research support provided by the faculty team of the College of Architecture and Urban Planning, Tongji University.

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

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