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Spatiotemporal Coordination between Human Capital Supply and Technological Innovation Actors

-- Spatial Linkages between Vocational Training Institutions and High-Tech Enterprises Based on POI Data

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Abstract: Addressing the skill–innovation coupling under industrial upgrading, this study leverages multi-source spatiotemporal data (2000–2023) on Shenzhen's vocational training institutions (VTIs) and high-tech enterprises (HTEs) to develop an integrated framework—panel time-series, two-perspective nearest-neighbor proximity, information-theoretic spatial-entropy decomposition, and Geodetector—for identifying the patterns, mechanisms, and differences of multiscale spatial coordination. The findings are as follows. (i) The temporal evolution of vocational training follows a four-stage nonlinear transition; spatial structure expands from core areas toward corridors and the periphery, highly consistent with city development strategies and indicative of spatial path dependence. (ii) The two-perspective proximity analysis reveals widespread coupling at walking scale, alongside marked sectoral differentiation: scientific research/information and business services exhibit high-frequency, short-chain, nearby coordination, whereas finance shows central-place concentration and supply–demand asymmetry with weaker firm-side proximity. (iii) Spatial-entropy decomposition uncovers clear scale effects: slight co-location at 100 m, a shift to misalignment at 200–500 m, and polycentric dispersion at 1–5 km, yielding a nested structure of micro-scale coordination and macro-scale dispersion. (iv) At the district level, two typical regimes emerge: enterprise agglomeration with education outreach in core areas, and dual high entropies with small differences in peripheral new towns. Geodetector further indicates polarized functional association: pairings related to life services, scientific research, and information technology have significantly higher q-values, while manufacturing-related pairings are weaker and more uncertain. Accordingly, we propose a policy toolbox aligned with a "globally dispersed—locally coordinated" logic that combines multiscale, industry-customized, and locationally stratified measures: embed high-frequency training and apprenticeships within cores/corridors; enhance accessibility in peripheral zones via satellite/mobile sites and TOD; and mitigate polycentric separation through cross-area course/hour recognition and in-house-training spillovers—thereby improving the fine-grained coupling of industrial and talent chains and strengthening system resilience.

Keywords: Vocational Training Institutions; High-tech Enterprises; Two-perspective Proximity; Spatial Association; Spatial-Entropy decomposition; Geodetector.

1. Introduction

With the advance of China's urbanization and industrial upgrading, vocational training—an essential institutional arrangement for enhancing human capital and sustaining high-quality regional development—has seen its spatial configuration and synergy with industry move to the forefront of scholarly inquiry. Vocational training institutions (VTIs) improve labor-market structure through knowledge diffusion and skills supply and, owing to spatial fit, facilitate the formation of regional innovation networks [1,2]. As a core city in the nation's innovation-driven strategy, Shenzhen is exemplary in both the spatial evolution of VTIs and the agglomeration of high-tech enterprises (HTEs); understanding their coordination mechanisms is therefore crucial for strengthening the coupling among education, industry, and innovation.

In terms of research progress, the focus on vocational training has evolved in phases. Early work emphasized institution-building and skill upgrading [3,4], followed by attention to digital transformation and regional coordination [5,6]. Internationally, the agenda has expanded from economic-effect evaluation to technological enablement and spatial heterogeneity[7–9]. Methodologically, a technology-driven, multidisciplinary toolkit has emerged—combining machine learning, service-quality evaluation, social network analysis, and spatial econometrics/GIS [10–13]—thereby deepening the dialogue between theory and policy practice via case studies and policy assessments.

Regarding mechanisms, the match between training and labor markets is jointly shaped by service quality, policy design, and technological enablement. When training content is misaligned with industrial demand, skills mismatch is likely to arise [14]; conversely, regional support networks and personalized programs can markedly improve employment outcomes [15,16]. Digital skills and lifelong learning are regarded as core strategies for coping with technological change [17,18]. Although subsidies and rule-of-law safeguards can expand coverage and enhance quality, resource allocation still needs to be optimized to account for regional disparities [19–21].

At the spatial level, the distribution of training resources and regional economies is uneven, with economic and policy orientations shaping pronounced patterns of agglomeration and mismatch [9,22–24]. Existing studies have used spatial autocorrelation and hot-spot detection to reveal education–

industry linkages, yet systematic quantification of nested, multiscale relations among firms, industrial chains, and urban networks—and of the spatiotemporal heterogeneity of policy interventions—remains limited.

Against this backdrop, there is a clear need—within Shenzhen's context—to identify and quantify VTI–HTE spatial coordination under a spatiotemporal big-data and spatial-econometric framework, thereby elucidating how skills supply matches innovation demand. On the one hand, a polycentric layout of VTIs together with HTE agglomeration may ease skills mismatch [25]; on the other hand, uneven resource distribution and quality differentials continue to constrain balanced development [20]. Accordingly, this study moves beyond static description to construct a spatiotemporal model of VTIs and HTEs, characterizing their matching regularities and coordination features, and thereby addressing theoretical and methodological gaps in the three-dimensional coordination of education–industry–space.

2. Research Framework

The socioeconomic context and the institutional–policy context jointly constitute the macro field within which vocational training institutions (VTIs) and high-tech enterprises (HTEs) co-evolve. The former reshapes the overall trajectory of industrial upgrading by influencing the supply–demand structure of human capital and the direction of factor flows; the latter—via entry regulation, fiscal support, and industrial planning—provides institutional safeguards for "training–industry" linkages. Superimposed, these forces form the foundational constraints and resource endowments of the system.

Within this macro framework, heterogeneous actors translate environmental conditions into concrete actions: VTIs choose locations based on market demand and policy incentives; HTEs make siting decisions according to industrial positioning and talent structures; governments and social organizations furnish institutionalized support through resource coordination, policy implementation, and interest mediation. As a result, the intra-urban spatial pattern evolves in phases—exhibiting differentiated dynamics of expansion, contraction, or relative stability—and recognizable distributional regularities emerge across functional subareas.

Functionally, we focus on demand matching and resource complementarity between "training" and "enterprise" along industrial chains and at the community scale. A combined toolkit—bivariate spatial autocorrelation, location-entropy combinations, and the Geodetector model—identifies high–high clusters, low–low depressions, and heterogeneous patterns, thereby revealing the spatial matching mechanisms linking industrial upgrading with skills supply and providing evidence for category-specific interventions.

Building on this, we introduce a dynamic-threshold classification model to delineate multi-level coordination types, while optimization of policies and resource allocation is used to enhance synergy. A triadic driver framework—"economic rank–industrial function–policy response"—is employed to interpret interregional interaction differences, which is coupled with a community-scale, two-dimensional typology of "resource allocation–functional synergy." On this basis, more targeted intervention schemes are proposed to remove factor barriers, reduce supply–demand mismatches, and promote coordinated upgrading.

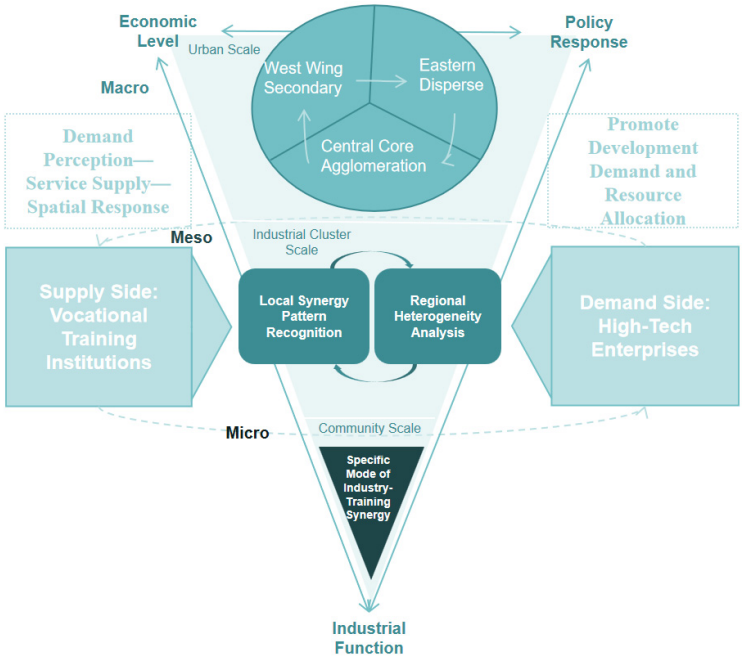


Figure 1. Research Framework

3. Data Sources and Methods

3.1. Study Area

Shenzhen is located in the southeastern Pearl River Delta, adjacent to Hong Kong, Dongguan, and Huizhou (113°43′–114°38′ E, 22°24′–22°52′ N). The city consists of ten districts: Futian, Nanshan, Luohu, Yantian, Bao'an, Longhua, Longgang, Guangming, Pingshan, and Dapeng. After four decades as a Special Economic Zone, Shenzhen has grown into a modern metropolis integrating commerce, tourism, finance, and industry, with a population of 13.02 million and a gross domestic product of CNY 242.2 billion. As a national hub of technological innovation, Shenzhen hosts 24,102 vocational training institutions and 18,849 high-tech enterprises. The total stock of skilled workers reaches 4.033 million, with the share of highly skilled workers rising to 38.5%—both among the highest nationwide—providing a crucial foundation for reform and development, advanced

manufacturing, and scientific progress. The municipal government has introduced a series of policy measures to support vocational education and high-tech industries. Given its concentration of high-tech activity, a comprehensive training system, and strong policy support, Shenzhen constitutes an ideal setting for examining the spatiotemporal evolution of vocational training and its spatial linkages with high-tech enterprises.

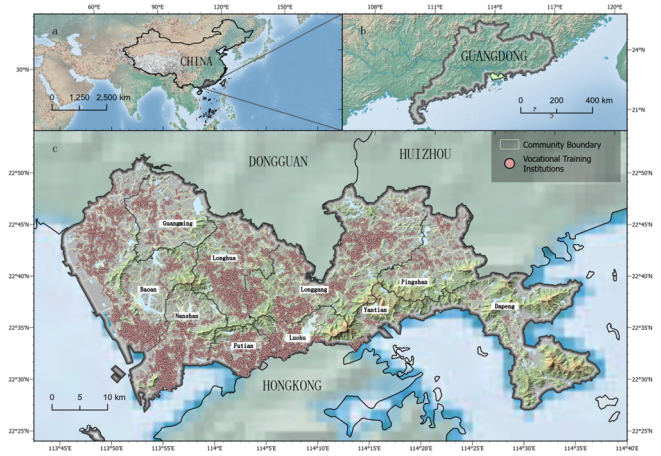


Figure 2. Study area and location.

3.2. Data Sources and Processing

The data architecture integrates multi-source, heterogeneous datasets spanning (i) entity information on vocational training institutions and high-tech enterprises, (ii) spatial–geographical data, and (iii) socioeconomic attributes. Core entity data were collected via Tianyancha APIs; after preprocessing, we retain 24,102 POI records for vocational qualification training institutions (including 5,815 deregistered entities). Cleaning used a quality-assessment framework with regex matching and business-rule validation to handle missing values, outliers, and duplicates.

(i) Geocoding: multi-stage geocoding based on standardized address feature vectors, batch-processed through the Amap Open Platform (v3 API); results validated via inverse-distance-weighted checks, removing coordinates with confidence <85%.

Table 1. Codes for Various Types of VTIs and HTEs.

Code	Type of Vocational Training	Code	Type of High-Tech Enterprise
A1	Financial Training	B1	Manufacturing Enterprise
A2	Scientific Research and Technical Service Training	B2	Scientific Research and Technical Service Enterprise
A3	Information Transmission, Software and Information Technology Service Training	B3	Information Transmission, Software and Information Technology Service Enterprise
A4	Modern Life Service Training	B3	Modern Life Service Enterprise
A5	Modern Commercial and Trade Service Training	B5	Modern Commercial and Trade Service Enterprise

(ii) Industrial classification: dual-standard fusion—GB/T 4754-2017 as the base mapped to the 2018 Statistical Classification of Modern Services; semantic analysis of business-scope text and keyword co-occurrence networks for optimization; five final categories: Finance (1,955), Scientific Research & Technical Services (8,916), Information Transmission/Software & IT Services (10,275), Modern Living Services (12,087), and Modern Business Services (16,604).

3.3. Research Methods

3.3.1. Two-Perspective Framework for Proximity Analysis

To characterize the spatial coupling between training and enterprises, we adopt a nearest-neighbor strategy and compute shortest Euclidean distances under two complementary perspectives.

(1) Training perspective (supply-side nearest neighbor). For each training site $t \in \mathcal{T}$, compute the Euclidean distance to its nearest high-tech enterprise $e \in \mathcal{E}$:

$$d_t^{(T\to E)} = \min_{e\in\mathcal{E}} \text{dist}(t,e) \quad (1)$$

This yields the distance sample $\{d_t^{(T\to E)}\} t \in \mathcal{T}$.

(2) Enterprise perspective (demand-side nearest neighbor). For each high-tech enterprise $e \in \mathcal{E}$, compute the Euclidean distance to its nearest corresponding training site $t \in \mathcal{T}$:

$$d_e^{(E\to T)} = \min_{t\in\mathcal{T}} \text{dist}(e,t) \quad (2)$$

This yields the distance sample $\{d_t^{(E\to T)}\} e \in \mathcal{E}$

3.3.2. Spatial-Entropy Decomposition

To quantify the degree of coupling vs. misalignment between vocational training institutions (class A) and high-tech enterprises (class B) across spatial scales, we adopt an information-theoretic spatial-entropy decomposition and build a triad of indicators: total entropy, spatial residual entropy, and local mutual information.

Let the categorical variable Z∈ {A, B} denote the actor class, and let $\{\omega_k\}$ be a set of distance bands representing multi-scale neighborhood relations. We obtain A/B point locations, project them to a metric coordinate system, and define annular (ring-buffer) neighborhoods for $\{\omega_k\} = \{100,200,300,500,1000,2000,5000\}$ m.Within each ring, we estimate the conditional class probabilities $P(z|\omega_k)$ from observed frequencies. We also estimate the global class probabilities $P(z)$ and compute the total entropy:

$$H(Z) = -\sum_{z\in Z} P(z)\ln P(z) \quad (3)$$

For each ω_k, we count A/B occurrences within the ring, estimate $P(z \mid \omega_k)$, and compute the spatial residual entropy at scale ω_k:

$$H(Z|\omega_k) = -\sum_{z\in Z} P(z|\omega_k)\ln P(z|\omega_k) \quad (4)$$

We then define the local mutual information curve as a function of scale:

$$\Delta I(\omega_k) = H(Z) - H(Z|\omega_k) \quad (5)$$

$\Delta I(\omega_k) > 0$ indicates co-location / positive coupling at scale. $\Delta I(\omega_k) < 0$ indicates relative dispersion / misalignment. We report $H(Z)$ (overall structural organization), and for each ω_k the pair $\{H(Z \mid \omega_k), \Delta I(\omega_k)\}$. A typical scale flip pattern—ΔI>0 at micro scales but ΔI<0 with increasing absolute magnitude at meso–macro scales—signals a transition from micro co-location to community/city-level misalignment and dispersion.

3.3.3. Geodetector

Geodetector assesses the explanatory power (q) of a factor

D for the spatial stratified heterogeneity of a target H (here, the distributions of VTIs/HTEs). The q-statistic is:

$$q_{D,H} = 1 - \frac{1}{n\delta^2}\sum_{H_{i=1}}^{m} n_{D,i}\,\delta_{H_{D,i}}^2 \quad (6)$$

where m is the number of strata (categories) defined by factor D; n is the total sample size; δ^2 is the global variance of H; $n_{D,i}$ and $\delta_{H_{D,i}}^2$ are the sample size and within-stratum variance of H for stratum i. The value range is $q \in [0,1]$; larger q indicates stronger explanatory power of D for the spatial distribution of VTIs/HTEs. Statistical significance is evaluated via Monte Carlo permutation (e.g., p<0.01); confidence intervals indicate estimation stability.

4. Spatially Differentiated Coordination between Vocational Training Institutions and High-Tech Enterprises

To characterize "training–enterprise" spatial coupling, we conduct a proximity analysis from two vantage points: a training perspective (distance from each VTI to its nearest HTE) and an enterprise perspective (distance from each HTE to its nearest corresponding VTI). We then summarize the overall pattern, sectoral differences, and spatial structure.

(i) Overall pattern: short-range dominance.From the training perspective, the nearest-neighbor distances to HTEs across the five sectors decline monotonically; the share within ≤500 m exceeds 94% for all sectors, and ≤100 m typically hovers around 50%. This indicates that training supply is deeply embedded within enterprise activity spaces, offering walking-scale accessibility and rapid matching capacity.

(ii) Enterprise perspective: heterogeneous dependence by sector.Using HTEs as the baseline, the proportion within ≤500 m ranges from 53% to 92%, showing marked variation. At still shorter ranges (≤300 m), Modern Business Services and Scientific Research & Technical Services reach 80.15% and 77.12%, respectively. Although the denominators differ between the two perspectives, both consistently reveal a robust pattern of nearby-proximity advantage with sectoral differentiation.

(iii) Sectoral characteristics and mechanisms. Scientific Research & Technical Services and Information Transmission/Software & IT Services form clusters and corridors within ≤300 m, reflecting high sensitivity to continuous skill updating, project collaboration, and knowledge spillovers. Modern Business Services is the closest under both perspectives, indicating deep embedding along commercial corridors and in mixed-use zones. Modern Living Services shows the next-best proximity, consistent with day-to-day skill provision for employees and communities. Finance displays asymmetry: strong proximity from the training side but weaker from the enterprise side, suggesting a central-place concentration with broad coverage yet insufficient firm-side adjacency.

(iv) Spatial structural gradient. Both perspectives indicate that ≤300 m dominates within core urban areas and industrial corridors, transitioning outward to 300–1000 m medium-to-far proximity; scattered cases >1000 m imply service gaps or lagged provision.

Overall, Shenzhen exhibits widespread coupling at walking scale and a clear "core–corridor–periphery" gradient. Differentiated siting and anticipatory (front-loaded) provision can further enhance the matching efficiency and resilience of the city's skills ecosystem.

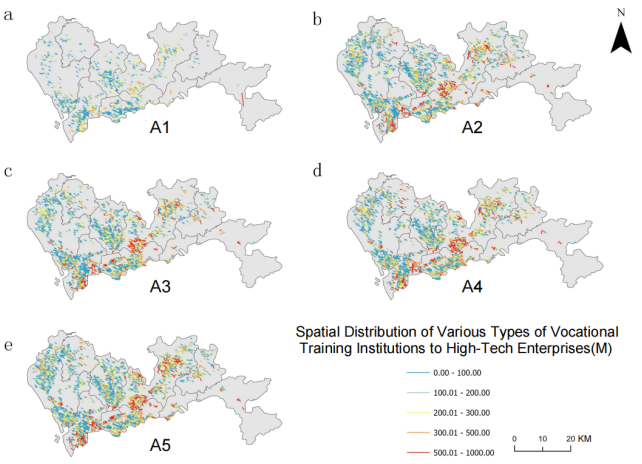


Figure 3. Spatial Distribution of Various Types of Vocational Training Institutions to High-Tech Enterprises.

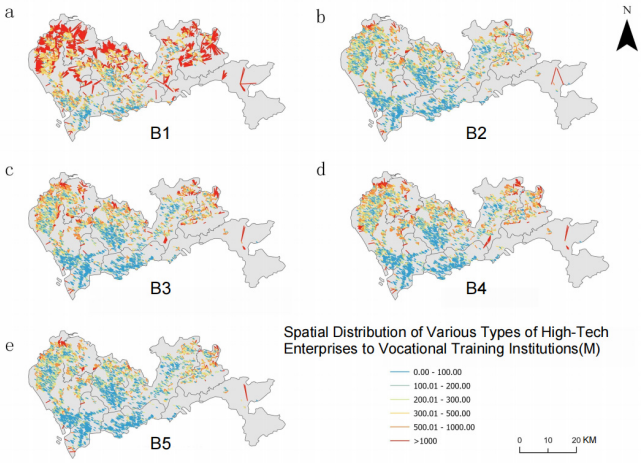


Figure 4. Spatial Distribution of Various Types of High-Tech Enterprises to Vocational Training Institutions.

Based on bivariate spatial autocorrelation, the citywide Moran's I for Shenzhen's vocational training institutions (VTIs) and high-tech enterprises (HTEs) is 0.070, indicating weak positive spatial autocorrelation between the two. To further reveal spatial heterogeneity, LISA clustering partitions Shenzhen into four local association types:

High–High clusters (8.13%) concentrated in Nanshan District, the western Bao'an area, and the Guangming–Longhua innovation corridor, where they show strong spatial coupling with high-tech industrial parks, universities, and research institutes. Low–Low clusters (0.96%) primarily in eastern Longgang, Pingshan, and Dapeng New Area, i.e., peripheral urban zones where both vocational education and high-tech industry are in a trough. Low–High outliers (8.20%) encircling the high–high core; HTEs are agglomerated but training supply lags. High–Low outliers (1.16%): scattered in the Longgang Vocational Education City and parts of Pingshan; vocational training resources are abundant but HTE density is low.

Building on the bivariate mapping, the "high–high" association areas can be refined into three spatial clusters that illustrate differentiated coordination pathways between VTIs and HTEs:HTE-led (Group 1) covering eastern Bao'an communities, with enterprise density significantly exceeding that of VTIs. Balanced coordination (Group 2) distributed across western Bao'an, Guangming, and parts of Longhua, where the counts of VTIs and HTEs are well matched. VTI-led (Group 3) centered on Nanshan and radiating toward

southern Bao'an; HTEs are relatively dispersed, with only a few communities showing localized agglomeration.

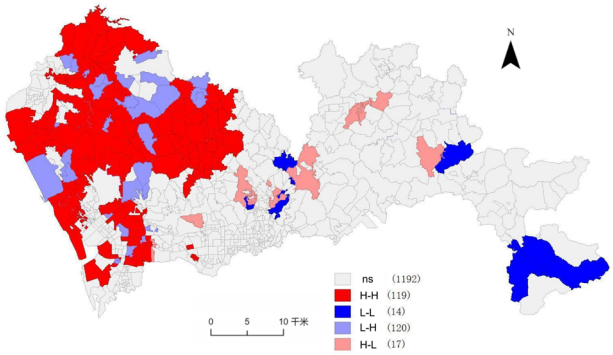


Figure 5. Bivariate Spatial Autocorrelation between Vocational Training Institutions and High-Tech Enterprises in Shenzhen.

5. Spatial-Entropy Characteristics and Scale Effects of Vocational Training and High-Tech Enterprises

To uncover how vocational training institutions (VTIs) and high-tech enterprises (HTEs) are coupled across scales, we adopt an information-theoretic spatial-entropy decomposition framework (Altieri et al.), and conduct systematic measurements and comparisons at the city – district – community levels.

For Shenzhen as a whole, the global spatial entropy of the two actor sets is only 0.00058, indicating strong spatial organization rather than randomness at the city scale. The scale-specific results exhibit a clear "three-segment" pattern.

At 100 m (ultra-local), spatial mutual information is positive — albeit small — signaling slight co-location consistent with micro-level needs for training to locate near labor demand. At the 200 – 500 m (community – block transition), mutual information switches from positive to negative and its absolute magnitude increases with distance, suggesting that functional zoning and land-price gradients accelerate relative dislocation between the two. At 1–5 km, residual entropy rises rapidly and negative mutual information expands, highlighting cross-subarea dispersion and a polycentric cluster structure. In short, weak co-location appears at micro scale, but misalignment and dispersion dominate at larger scales.

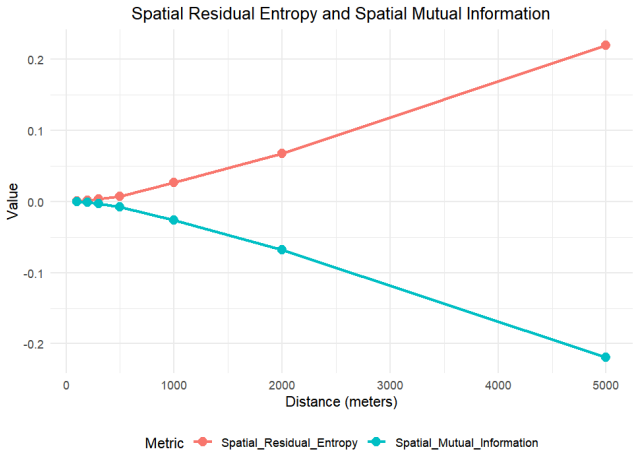


Figure 6. Spatial-entropy decomposition

At the district level, we further estimate spatial entropy for VTIs and HTEs separately and use the difference (VTI entropy − HTE entropy) to characterize relative dispersion. Overall, outer new towns—Bao'an, Longgang, Longhua, and Pingshan—show higher and broadly similar entropies for both actors, implying relatively balanced diffusion and stronger consistency. By contrast, core and coastal districts—Nanshan, Dapeng, Luohu, Futian, and Yantian—tend to exhibit a "enterprise-intensive, education-outreaching" structure: HTEs are tightly concentrated by parks and high-end business carriers, while VTIs cover a wider service hinterland. Notably, Guangming, though emerging, shows VTIs that are relatively more dispersed and HTEs slightly more concentrated, consistent with its mixed industrial-new-town and residential morphology. These contrasts reveal coexistence of coupling and misalignment between industrial functional zones and educational service hinterlands: core areas leverage enterprise agglomeration supported by educational spillovers, whereas peripheral areas approach synchronous diffusion and spatial co-progress.

Table 2. District-level summary (illustrative statistics)

District	Number of VTIs	Number of HTEs	Spatial entropy
Baoan	4426	7014	0.667
Futian	4045	940	0.484
Guangming	768	1982	0.592
Longgang	4808	1719	0.577
Longhua	2973	3411	0.691
Luohu	1559	469	0.541
Nanshan	4816	2415	0.637
Pingshan	458	857	0.646
Yantian	249	42	0.413

Synthesizing the multi-scale evidence, we draw two conclusions. First, at the city level the two actor sets are highly structured; weak ultra-local co-location fades quickly with scale and transitions into dispersion. Second, at the district scale two typical regimes emerge: (i) a "core-area enterprise agglomeration with education outreach" pattern; and (ii) "dual high entropies with small differences" in peripheral new towns—consistent with distinct development stages and functional positioning, hence requiring differentiated coordination strategies.

Policy implications by scale:100–300 m (micro): promote embedded park- and block-level training points and apprenticeship sites;500 – 2,000 m (community – block): enhance industry–training accessibility via active-mobility networks, TOD, and corridor-based spatial organization;1–5 km (city): deploy cross-subarea coordination, cross-district credit/hour recognition, and in-house-training spillover mechanisms to mitigate separation under a polycentric pattern. A multi-scale toolbox thus preserves enterprise agglomeration advantages while improving the spatial fit and service efficiency of vocational education for the innovation economy.

6. Regional Heterogeneity and Coordination Patterns of Functional Association

Based on Geodetector results, we identify pronounced regional heterogeneity and coordination patterns in the functional association between vocational training institutions (VTIs) and high-tech enterprises (HTEs) at both the citywide scale and within subarea groups. The spatial association exhibits a marked bipolar tendency: high-association pairings in life services, scientific research, and information technology stand in sharp contrast to low-association pairings in traditional manufacturing.

(i) High-association pairings. The synergy between life-service HTEs and financial vocational training is particularly salient, with a citywide q=0.780. The group-style layout of finance and life services in core urban areas further reflects the bidirectional demand for composite services in talent-dense locations. In addition, scientific-research HTEs show strong ties with IT vocational training and life-service vocational training , underscoring the spatial stickiness of research–industry–education integration under innovation-driven development. Although the q-values for business-service vocational training with life-service HTEs and IT vocational training with IT HTEs are slightly lower than the foregoing pairs, they remain well above the citywide median, highlighting the spatial concentration of training demand in the IT domain.

(ii) Regional decomposition. High-association q-values display differentiated core drivers across groups. For example, life-service HTEs × financial vocational training reaches in Group 2, significantly higher than Group 1 and the citywide value, indicating the strongest agglomeration effect of financial services in Group 2. The scientific-research × IT-training pairing in Group 2 also peaks at , which is 33.4% higher than Group 3 , further characterizing Group 2 as the regional innovation core. By contrast, manufacturing × technology-training shows extreme divergence: in Group 1 the manufacturing-HTE × research-training pairing attains, whereas in Group 2 and Group 3 it drops to 0.042 and 0.008, respectively—evidence of highly uneven concentration versus dispersion of technology-training demand across regions.

(iii) Low-association pairings. Manufacturing HTEs exhibit weak functional links with financial training and IT training, amounting to only 34.6%–43.8% of the corresponding high-association levels. This likely reflects relative delays in digital and upmarket transformation within manufacturing, which has constrained the release of demand for high-skill training. The q-values for manufacturing HTEs × life-service training are slightly higher but still fall within the bottom decile of the overall distribution, further confirming weak spatial association between manufacturing and vocational training.

(iv) Stability and gradients. The confidence-interval width of low-q pairings (mean 0.085) is notably larger than that of high-q pairings (mean 0.043), implying greater uncertainty in the spatial association patterns of the former. Spatial synergy between VTIs and HTEs not only shows a clear high–low polarization across the city but also exhibits distinct regional gradients across groups: Group 2 is driven by a dual core of services and science–technology; Group 1 centers on manufacturing-oriented technological upgrading; and Group 3 ranks lower in both strength and stability of association. These findings provide theoretical grounding and empirical evidence for optimizing regional industrial layout and allocating training resources.

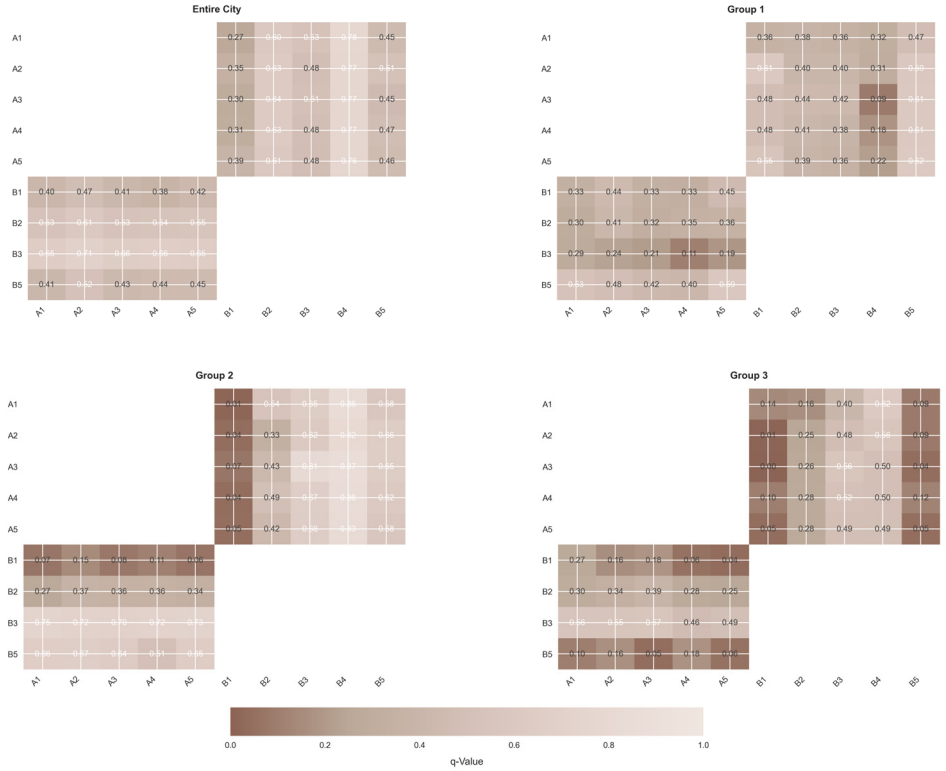


Figure 7. Heat Map of Combined q-Values for Vocational Training and High-Tech Enterprises in the Entire City and Its Various Groups

7. Conclusion

Drawing on the data and methods developed above, and triangulating evidence from the two-perspective nearest-neighbor analysis, the information-theoretic spatial-entropy decomposition, and Geodetector tests, this study delineates the spatial coupling between vocational training institutions (VTIs) and high-tech enterprises (HTEs) in Shenzhen.

Distance distributions from VTIs to HTEs exhibit a pronounced walking-scale profile, indicating deep supply-side embedding within demand hinterlands. Using enterprises as the baseline reveals sector-specific dependence: scientific research/information and business services tend toward high-frequency, short-chain, face-to-face collaboration, whereas finance reflects a central-place concentration and a coverage-oriented supply structure. Although the two perspectives use different denominators, they jointly indicate that coordination is not accidental but a structural outcome jointly driven by knowledge-update velocity, task organization, and economies of scale.

In core districts and industrial corridors, short-range links dominate; toward the periphery, distances increase rapidly and scattered or lagged connections appear. This continuous gradient is not explained by distance alone; it co-varies with functional density, mixed-use intensity, and transport connectivity. The stronger the nodes, the lower the friction for information and skills flows, and the higher the training–enterprise matching efficiency. In this sense, spatial structure constitutes an implicit constraint on institutional efficiency.

Spatial-entropy decomposition shows slight co-location at micro scales; at block–community scales, mutual information changes sign from positive to negative and grows in magnitude with distance; at the city scale, a polycentric, dispersed pattern prevails. Thus, "nearby coordination" and "cross-subarea dispersion" are not contradictory but nested responses of the same system at different scales. Ignoring this scale transition risks policy misalignment—i.e., applying micro-effective tools at macro scales.

District-level entropy and entropy differences reveal two typical regimes: enterprise agglomeration with education outreach in core/coastal areas, and near-synchronous diffusion in peripheral new towns. Emerging areas such as Guangming—with mixed industrial-new-town and residential forms—show more dispersed training and slightly more concentrated enterprises. Hence, industrial functional zones and educational service hinterlands do not simply overlap; coupling and misalignment co-exist across development stages and carrier conditions.

Geodetector results show that service–science chains (e.g., life services × financial training, research × IT training) display stronger functional stickiness and tighter confidence bands, whereas manufacturing-related pairings are generally weaker and more uncertain. At the cluster scale, dual-core (services + sci-tech) regions exhibit stronger associations; manufacturing × research-training varies sharply across groups, indicating spatially asynchronous technological upgrading and innovation-supply capacity. The industry–region interaction is thus the critical lens for interpreting coordination strength.

Policies should avoid one-size-fits-all approaches and instead use combinational strategies to enhance matching efficiency and system resilience. Micro (100–300 m): deploy embedded training/apprenticeship workshops within cores/corridors; use modular short courses and certificate fast-tracks to support high-frequency iteration. Meso (500–2,000 m): organize corridor-based commuting via TOD + active-mobility networks; in peripheral areas, add satellite/mobile sites to reduce effective distance, prioritizing skill-sensitive industries. City (1–5 km): establish cross-subarea course/hour recognition and in-house-training spillover mechanisms to mitigate separation under polycentricity; channel financial training outward along industrial axes; for research/IT/business services, emphasize on-the-job iteration and joint training; for manufacturing, link demonstration parks with high-quality training and precision skill profiling to shorten transformation lags. Consolidate core agglomeration and optimize spillovers; in outer new towns, densify sites and improve accessibility to achieve coordinated diffusion.

This study prioritizes association identification. Future research could strengthen causal inference using quasi-experiments, event studies, DID or synthetic control; incorporate policy shocks and structural change over time; conduct systematic robustness checks for MAUP and threshold sensitivity; and deepen industry granularity and behavior–outcome linkages by integrating mobile signaling, job postings, course profiling, and firm performance to complete the "spatial coordination to socio-economic effects" evidence chain.

Overall, Shenzhen's industry–education relationship features micro-scale nearby coordination nested within macro-scale polycentric dispersion. The strength of coordination is jointly shaped by industry chains, spatial structure, and regional development stage. A multi-scale governance + industry customization + locational stratification toolbox can preserve enterprise agglomeration advantages while improving the spatial fit, matching efficiency, and system resilience of vocational education—thereby offering actionable policy pathways for innovation-driven and high-quality development.

Acknowledgments

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