Spatial Structure and Evolution of AI Labor Demand in China: Evidence from Job Advertisements

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Abstract. This paper examines the spatial and temporal evolution of Artificial Intelligence (AI)-related labor demand across Chinese cities using large-scale online job advertisement data from 2016 to 2025. We construct a city-year-skill tensor of AI job postings and apply a Bayesian Canonical Polyadic (CP) decomposition to uncover latent structures in the AI labor market. To complement the latent factor analysis, we compute revealed comparative advantage (RCA) measures to identify city-level specialization patterns and use TF-IDF-based cosine similarity to analyze convergence and differentiation in AI skill demand across cities over time.

The results reveal a highly concentrated AI labor market centered around Beijing, Shanghai, Shenzhen, Guangzhou, and Hangzhou, which consistently exhibit similar demand for core AI skills. In contrast, secondary cities display more heterogeneous and application-oriented specialization patterns. Similarity analysis further indicates increasing convergence in AI skill demand across cities during the rapid expansion phase of the AI sector, followed by signs of renewed differentiation in recent years. Overall, the findings highlight the coexistence of spatial concentration and functional diversification in China's evolving AI economy.

Keywords: Artificial intelligence labor markets · Economic geography · Tensor decomposition · Regional specialization

1 Introduction

The rapid diffusion of artificial intelligence (AI) technologies is reshaping labor markets worldwide, altering both the composition of employment and the geography of economic opportunity. Demand for AI-related skills is highly uneven across regions and evolves alongside technological change, industrial upgrading, and digital transformation. Understanding how AI labor demand develops across space and time is therefore important for assessing the broader implications of the AI transition for regional inequality and digital inclusion.

These issues are particularly salient in large and internally diverse developing economies. China provides an especially informative setting due to its rapid expansion in digital infrastructure, strong state support for AI development, and growing technology sector over the past decade. At the same time, substantial

differences persist across Chinese cities in industrial structure, innovation capacity, and access to high-skilled employment. As a result, the spatial evolution of AI-related labor demand in China offers insight into how emerging digital economies may reinforce or reshape existing regional disparities.

In this paper, we analyze the evolution of AI-related labor demand across Chinese cities using a large-scale dataset of online job advertisements spanning 2016–2025. We construct a city–year–skill representation of the AI labor market that captures the joint dynamics of geographic location, time, and AI skill categories. This framework allows us to examine not only where AI-related employment is concentrated, but also how urban AI ecosystems evolve and relate to one another over time.

Our empirical analysis combines three complementary approaches. First, we apply a Bayesian Canonical Polyadic (CP) tensor decomposition with a Poisson likelihood to uncover latent structure in the city–year–skill interaction space. The decomposition identifies interpretable components linking groups of cities, temporal trajectories, and clusters of AI skills. Second, we construct revealed comparative advantage (RCA) measures to characterize patterns of relative specialization in AI-related skills across cities and years. Third, we analyze inter-city similarities based on AI skill demand profiles in order to study convergence, clustering, and diffusion within the AI economy. Combining these perspectives allows us to characterize both concentration and diffusion processes within China's emerging AI economy.

Our findings reveal a highly concentrated geography of AI labor demand centered around a small number of dominant metropolitan hubs, particularly Beijing, Shanghai, Shenzhen, Guangzhou, and Hangzhou. At the same time, we observe gradual diffusion of AI-related skill demand into secondary and inland cities, accompanied by increasing diversification in AI application domains such as smart agriculture, intelligent transportation, financial technology, and AI-enabled healthcare. Similarity analysis further suggests that while many cities increasingly adopted skill profiles resembling those of leading technology hubs during the rapid expansion phase of the AI sector, more recent years exhibit signs of renewed differentiation and specialization.

The main contribution of this paper is empirical and descriptive. Using large-scale online recruitment data, we provide a systematic characterization of the spatial and temporal evolution of AI-related labor demand across Chinese cities. More broadly, the paper contributes to understanding how technological transformation interacts with regional inequality and digital inclusion in the context of a large developing economy.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodological framework. Section 4 describes the dataset and reports the empirical results. Section 5 concludes with a discussion of the broader implications of the findings.

2 Related Literature

This paper builds on and contributes to three strands of the literature: (i) the measurement of labor market demand using online vacancy data, (ii) methods for analyzing specialization and spatial structure in economic geography, and (iii) tensor factorization and latent structure learning in high-dimensional count data.

First, a large and growing literature uses online job postings to measure labor demand and skill requirements in real time (3; 5). Studies in labor economics have used job advertisements to construct measures of skill demand, occupational upgrading, and technological change, particularly in the context of digitalization and automation (4; 15). More recent contributions exploit large-scale online recruitment platforms to analyze emerging skill requirements in artificial intelligence and data-intensive technologies (9; 16). Our dataset, constructed from major Chinese job platforms, follows this approach by using keyword-based identification of AI-related vacancies to measure the evolution of AI labor demand across cities and time.

Second, this paper relates to the literature on regional specialization, economic geography, and spatial clustering of high-skill industries (7). A central theme in this literature is that economic activity is unevenly distributed across space and that regions exhibit persistent specialization patterns driven by agglomeration economies, knowledge spillovers, and labor market pooling. The revealed comparative advantage (RCA) framework (1) has been widely used to quantify relative specialization across regions and industries, and has been extended in numerous applications in trade and regional science. Our analysis of RCA measures contributes to this literature by documenting the evolution of AI-related specialization across Chinese cities and highlighting the increasing diversification of AI applications across regions.

Third, our methodological approach connects to the literature on network analysis, similarity measures, and tensor factorization for uncovering latent structure in complex economic systems. Cosine similarity and TF-IDF weighting have been widely used in information retrieval and computational social science to construct interpretable measures of similarity between high-dimensional profiles. In parallel, tensor decomposition methods provide a powerful framework for modeling multiway data and extracting latent factors that vary across multiple dimensions such as space, time, and attributes. Canonical Polyadic (CP) decomposition, in particular, has been extended to count-valued data through Poisson and Bayesian formulations (8; 6), enabling principled inference in settings involving sparse and heterogeneous event counts. Our use of a Bayesian Poisson CP model builds directly on this literature, allowing us to jointly model city-year-skill interactions and uncover latent structures in AI labor demand with uncertainty quantification.

Finally, our paper contributes to the emerging literature on the geography and structure of AI labor markets (2; 10). Existing studies have documented the rapid expansion of AI-related employment, the concentration of AI activity in leading innovation hubs, and the diffusion of AI technologies across sectors and

regions. However, less is known about how the structure of AI skill demand co-evolves across cities and how similarity and specialization patterns evolve over time. We provide a unified framework for analyzing both latent structure and observable specialization in AI labor demand.

3 Methodology

3.1 Bayesian Canonical PARAFAC Decomposition

Identifying interpretable latent structures in high-dimensional multiway data is a central challenge in the analysis of polyadic relationships among multiple sets of entities. Tensor factorization methods (8) provide a powerful framework for uncovering such latent patterns. Given that our data consist of nonnegative count observations, we employ a Bayesian tensor factorization approach specifically designed for count-valued data (6).

Following (6), we model the evolution of AI-related labor demand as a third-order tensor that captures interactions among cities, years, and AI skill categories. Let $\mathbf{X} \in \mathbb{N}^{N_c \times N_t \times N_s}$ denote the observed count tensor, where each entry corresponds to the number of AI-related job advertisements associated with city c, year t, and skill category s.

We assume that $\mathbf{X}$ admits a low-rank Canonical Polyadic (CP) decomposition under a Poisson likelihood. Formally, each tensor entry is modeled as

$$x_{ijk} \sim \text{Pois}\left(\sum_{r=1}^{R} \lambda_r u_{ir}^{(c)} u_{jr}^{(t)} u_{kr}^{(s)}\right),$$

where R denotes the number of latent components, λ_r represents the weight of component r, and $u^{(c)}$, $u^{(t)}$, and $u^{(s)}$ are nonnegative factor matrices associated with cities, years, and skills, respectively.

To enable probabilistic inference, we adopt the Bayesian formulation developed by (6). Specifically, Dirichlet priors are imposed on the factor matrices, while the component weights follow hierarchical Gamma-Beta priors. This hierarchical specification yields a fully generative framework for count-valued tensor data and facilitates uncertainty quantification for the inferred latent structures.

Posterior inference is conducted using a Gibbs sampling algorithm based on data augmentation techniques. The inferred posterior distributions over latent components jointly characterize patterns of regional clustering, temporal dynamics, and skill co-occurrence within AI-related labor demand. These latent structures subsequently serve as the basis for examining regional specialization, structural similarity across cities, and the evolving dynamics of digital inclusion in the AI-driven labor market.

3.2 Revealed Comparative Advantage

To examine patterns of specialization in AI-related labor demand, we construct a revealed comparative advantage (RCA) index (1) for each city, year, and AI

skill category using job advertisement counts. The RCA measure is commonly employed in the fields of economic geography and international trade to assess whether a region demonstrates a relative specialization in a particular activity compared with a broader benchmark system (12; 14).

Let X_{ctk} denote the number of job advertisements associated with city c, year t, and AI skill category k. The RCA index is defined as

$$\mathrm{RCA}_{ctk} = \frac{\dfrac{X_{ctk}}{\sum_k X_{ctk}}}{\dfrac{\sum_c X_{ctk}}{\sum_{c,k} X_{ctk}}}.$$

The numerator represents the share of skill category k within the AI labor demand composition of city c in year t, whereas the denominator captures the corresponding national share of that skill category during the same period. Accordingly, the RCA index evaluates whether a given AI skill is more heavily concentrated within a city relative to its overall prevalence across all cities.

An RCA value exceeding one indicates that a city possesses an above-average specialization in a particular AI skill compared with the national distribution in that year, whereas values below one imply below-average specialization.

The RCA analysis complements the tensor decomposition framework. Whereas the Bayesian CP decomposition identifies latent multidimensional structures embedded in the city–year–skill interaction tensor, the RCA index offers a transparent and interpretable measure of relative specialization. Taken together, these approaches enable an integrated examination of both latent structural dynamics and observable comparative advantages in the evolution of AI-related labor demand across Chinese cities.

3.3 TF-IDF-Based Similarity Between Cities

To investigate the evolving similarity structure of AI-related labor demand across cities, we construct year-specific similarity matrices based on the distribution of AI skill-related job advertisements. This approach enables an examination of the extent to which cities exhibit similar AI skill demand profiles and how these relationships evolve over time.

Let X_{ctk} denote the number of job advertisements associated with city c, year t, and AI skill category k, consistent with the tensor $\mathbf{X} \in \mathbb{N}^{N_c \times N_t \times N_s}$ defined previously. For each year t, we extract the city–skill slice $\mathbf{X}^{(t)} \in \mathbb{R}^{C \times K}$ with entries $X_{ck}^{(t)} = X_{ctk}$.

To reduce the influence of highly prevalent skills and emphasize relatively distinctive skill profiles, we apply term frequency–inverse document frequency (TF–IDF) weighting (13; 11) to each yearly matrix $\mathbf{X}^{(t)}$. In this setting, cities are treated as documents and AI skills as terms. The resulting TF–IDF transformed matrix is denoted by $\widetilde{\mathbf{X}}^{(t)}$.

For each year t, we compute cosine similarity between city profiles based on the rows of $\widetilde{\mathbf{X}}^{(t)}$. Specifically, for cities i and j,

$$S_{ij}^{(t)} = \frac{\widetilde{\mathbf{X}}_{i\cdot}^{(t)} \cdot \widetilde{\mathbf{X}}_{j\cdot}^{(t)}}{\left\|\widetilde{\mathbf{X}}_{i\cdot}^{(t)}\right\| \left\|\widetilde{\mathbf{X}}_{j\cdot}^{(t)}\right\|},$$

where $\widetilde{\mathbf{X}}_{i\cdot}^{(t)}$ denotes the i-th row of $\widetilde{\mathbf{X}}^{(t)}$. The resulting similarity matrix $\mathbf{S}^{(t)} \in [0,1]^{N_c \times N_c}$ captures the similarity of AI skill demand structures across cities in year t.

To analyze the hierarchical structure of the AI labor market, cities are ranked according to their total number of AI-related job advertisements aggregated over all years and skills, i.e.,

$$X_c = \sum_{t,k} X_{ctk}.$$

The five cities with the highest values of X_c are defined as leading AI labor market centers, while the remaining cities form a comparison group. Using the yearly similarity matrices, we compute three aggregate measures: (i) average similarity among leading cities, (ii) average similarity among non-leading cities, and (iii) average similarity between the two groups.

These measures provide a dynamic characterization of convergence and divergence in AI-related labor demand across urban systems. Increasing within-group similarity among leading cities may indicate consolidation of specialized AI hubs, while rising cross-group similarity may reflect broader diffusion of AI capabilities and convergence in labor market structures. Conversely, declining cross-group similarity may signal increasing stratification in participation within the AI economy.

This TF–IDF-based similarity analysis complements both the tensor decomposition framework and the RCA measures. Whereas the Bayesian tensor model uncovers latent multidimensional structure and the RCA framework captures relative specialization, the similarity analysis focuses on relational structure, revealing how cities cluster and evolve in the space of AI-related skill demand.

4 Results

4.1 Data and Descriptive Analysis

The dataset used in this study is obtained from Macrodatas [1], which aggregates and curates large-scale online recruitment data from major Chinese job platforms, including BOSS Zhipin, 51job, Zhaopin, Liepin, and Lagou. The underlying data are constructed from keyword-based identification of artificial intelligence–related job postings, following standard practices in the labor economics literature for measuring skill-specific labor demand from online vacancy data.

[1] https://www.macrodatas.cn/article/1147473564

The dataset spans the period from 2016 to March 2025 and contains detailed information on job titles, job descriptions, and geographic locations. This rich structure enables the construction of a harmonized city–year–skill dataset capturing the evolution of AI-related labor demand across Chinese cities over time. In total, the dataset comprises 1,602,437 AI-related job advertisements.

To provide a descriptive overview of the spatial evolution of AI labor demand, Figure 4.1 visualizes the distribution of AI-related job advertisements across Chinese cities from 2016 to 2024. The figure indicates that in the early period, AI job postings were highly concentrated in coastal regions and major metropolitan centers, particularly Beijing, with relatively limited penetration into inland cities. Over time, however, the geographic distribution becomes more dispersed, with a gradual increase in AI-related job activity in inland regions, suggesting a slow but observable diffusion of AI labor demand beyond the initial coastal concentration.

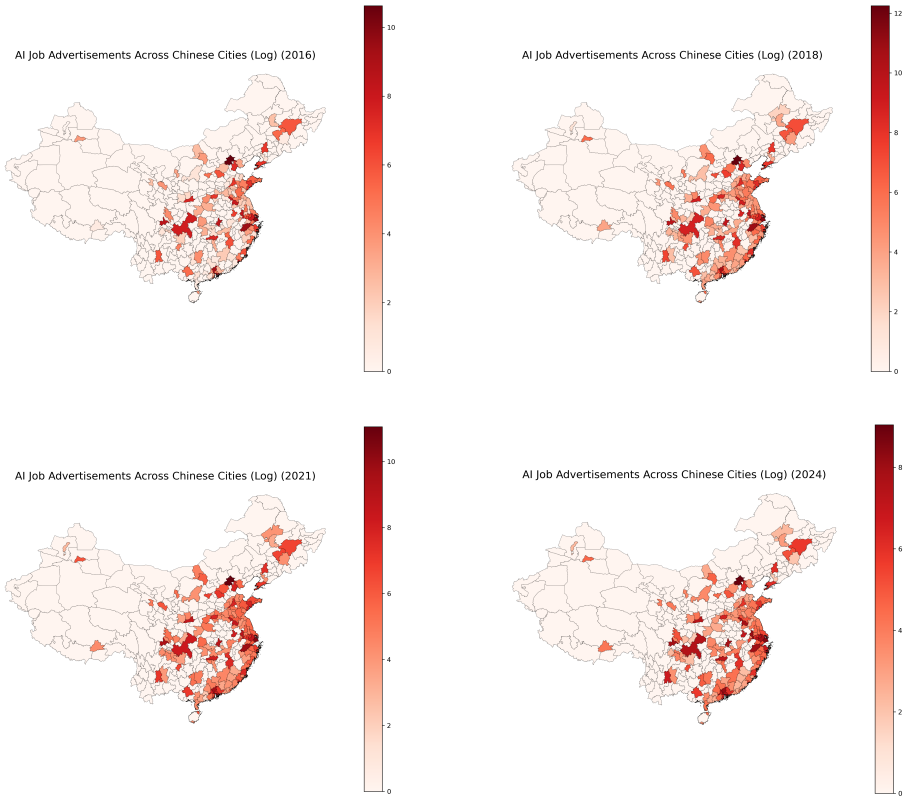

Fig. 1. Spatial evolution of AI-related job advertisements across Chinese cities, 2016-2024.

4.2 Bayesian Canonical PARAFAC Decomposition

We estimate a Bayesian Canonical PARAFAC decomposition model with $R = 50$ latent components. Choosing a relatively large number of components allows the model to flexibly accommodate heterogeneous and potentially overlapping patterns in the city–year–skill interaction structure, while the Bayesian prior imposes regularization by shrinking the contribution of less relevant components toward negligible levels. This specification enables a rich representation of complex dynamics in AI-related labor demand without imposing restrictive assumptions on the underlying number of latent factors.

The estimated latent components are summarized using a tripartite network representation in Figure 4.2. We focus on the five components with the largest posterior mean weights, which are represented as nodes in the network. For each selected component, we report the top five cities and top five AI skill categories most strongly associated with the corresponding latent factor.

Figure 4.2 reveals a pronounced geographical concentration of AI-related labor demand in China. Across nearly all dominant components, the leading cities are consistently Beijing, Shanghai, Shenzhen, Guangzhou, and Hangzhou, underscoring the central role of these major innovation hubs in shaping China's AI labor market. This pattern aligns with established findings in the literature on agglomeration economies and technological clustering, which emphasize that high-skill industries tend to concentrate in locations with advanced digital infrastructure, dense research ecosystems, and deep labor pools. At the same time, the presence of Nanjing in some components suggests the gradual emergence of secondary innovation centers participating in the expansion of AI-related employment.

The dominant skill categories include machine learning, deep learning, cloud computing, data mining, big data platforms, and natural language processing, indicating that labor demand is primarily concentrated in core enabling technologies of the contemporary AI ecosystem.

We further examine the temporal evolution of the estimated CP components by analyzing their time-mode loadings in Figure 3. These trajectories highlight the dynamic nature of AI labor demand over the sample period. In particular, most components exhibit strong associations with the period between 2017 and 2021, reflecting a phase of rapid acceleration in AI investment and hiring activity.

4.3 Revealed Comparative Advantages of Cities

We compute RCA scores for all city-skill pairs over the period 2016–2025 to identify patterns of relative specialization in AI-related labor demand. For illustration, Figure 4 presents heatmaps for 2019, 2021, and 2023, focusing on the ten cities and ten AI skill categories with the highest RCA values in each year. These visualizations provide an interpretable overview of how cities develop distinct AI specialization profiles over time.

The results reveal substantial geographic heterogeneity in AI-related skill demand and indicate increasing diversification in AI application domains. In 2019,

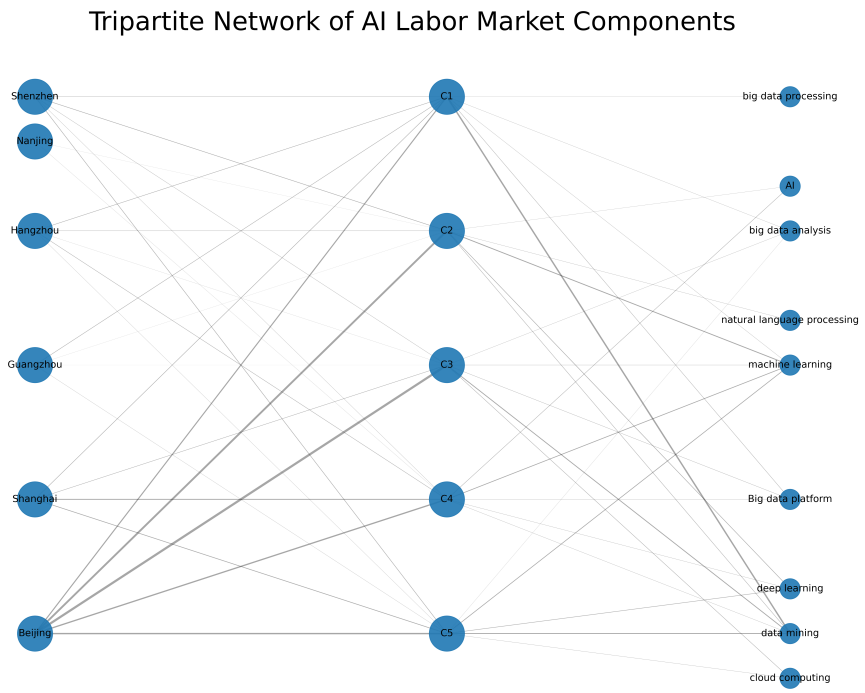

Fig. 2. Tripartite structure of latent AI labor market components. Nodes on the left represent cities, nodes in the center represent latent CP components, and nodes on the right represent AI skill categories.

cities such as Weifang, Yantai, Luoyang, and Urumqi exhibit strong specialization in smart agriculture, reflecting the growing integration of AI technologies into agricultural modernization and rural industrial upgrading. By 2021, Wenzhou displays comparative advantage in human–machine collaboration technologies, while Xuzhou specializes in smart elderly care, potentially linked to demographic pressures and the expansion of AI-enabled healthcare services.

By 2023, specialization patterns become increasingly application-oriented and sector-specific. Wenzhou is associated with augmented intelligence, Yantai with smart banking technologies, Quanzhou with smart transportation systems, and Haikou with smart education. Overall, the RCA patterns suggest that the diffusion of AI technologies in China extends beyond the major technology hubs and increasingly reflects local industrial structures, policy priorities, and region-specific development strategies.

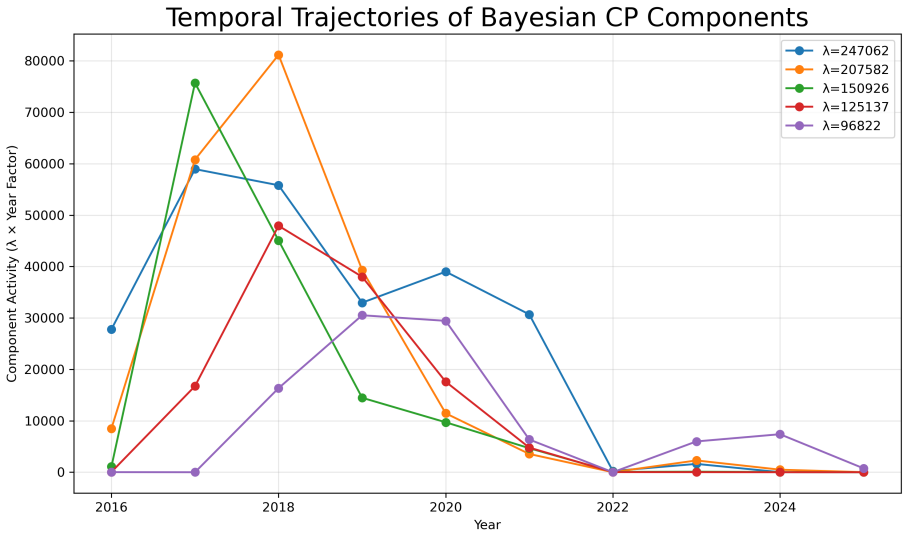

Fig. 3. Temporal evolution of Bayesian CP components, 2016-2025.

4.4 TF-IDF-Based Similarity Between Cities

The similarity analysis reveals a highly hierarchical geography of AI-related labor demand across Chinese cities. The five leading cities-Beijing, Shanghai, Shenzhen, Hangzhou, and Guangzhou-consistently exhibit extremely high pairwise similarity throughout the study period, with average cosine similarity values generally above 0.94 and reaching nearly 0.98 in several years. This indicates that the major AI hubs share highly comparable AI skill demand structures, reflecting common specialization in foundational technologies such as machine learning, deep learning, cloud computing, and big data systems. The persistence of these high similarity levels suggests strong convergence among the leading metropolitan AI ecosystems and underscores the concentration of advanced AI capabilities within a small set of dominant innovation centers.

At the same time, the evolution of similarity among non-leading cities and between leading and non-leading cities points to broader processes of diffusion and stratification within the AI economy. Between 2016 and 2023, average similarity among non-top-five cities increases substantially from 0.69 to 0.88, while similarity between the top-five and remaining cities rises from 0.75 to 0.89. These trends suggest that AI-related labor demand became increasingly standardized and geographically widespread during the rapid expansion of China's AI sector. In particular, secondary cities gradually developed AI skill demand profiles that more closely resembled those of the major technology hubs.

However, the decline in both within-group and cross-group similarity observed in 2024 and 2025 may indicate renewed differentiation across local AI labor markets. This pattern potentially reflects increasing specialization, uneven

industrial upgrading, or broader macroeconomic adjustments shaping regional trajectories of AI development.

5 Discussion and Conclusion

This paper examines the spatial and temporal evolution of AI-related labor demand across Chinese cities between 2016 and 2025 using large-scale online job advertisement data. Combining Bayesian CP tensor decomposition, RCA measures, and TF-IDF-based similarity analysis, we provide complementary perspectives on latent structure, regional specialization, and inter-city relationships within China's emerging AI economy.

Across all empirical approaches, the results reveal a highly structured yet evolving geography of AI-related labor demand. The tensor decomposition identifies a persistent concentration of AI capabilities within a small number of dominant metropolitan centers–particularly Beijing, Shanghai, Shenzhen, Guangzhou, and Hangzhou–which consistently exhibit strong demand for foundational AI skills such as machine learning, deep learning, cloud computing, and big data technologies. These findings suggest that advanced AI development in China remains strongly anchored in major innovation hubs characterized by dense research ecosystems, digital infrastructure, and deep high-skill labor markets.

At the same time, the RCA analysis demonstrates substantial heterogeneity outside these leading cities. Secondary and inland cities increasingly exhibit specialization in more application-oriented AI domains, including smart agriculture, intelligent transportation, smart banking, elderly care technologies, and smart education. This pattern indicates that the diffusion of AI-related labor demand is shaped not only by technological capabilities, but also by local industrial structures, demographic conditions, and region-specific development priorities. Rather than converging toward a single uniform model of AI development, Chinese cities appear to integrate AI technologies in ways that reflect their existing comparative advantages and economic contexts.

The similarity analysis further highlights a dynamic interplay between convergence and differentiation. While the leading AI hubs remain highly similar throughout the study period, non-leading cities become progressively more similar both to each other and to the dominant centers between 2016 and 2023, suggesting broad diffusion of AI-related capabilities across urban China during the rapid expansion phase of the AI sector. However, the modest decline in similarity observed in the most recent years may indicate the emergence of renewed differentiation as regional AI ecosystems mature and become increasingly specialized.

Taken together, the findings point to the coexistence of spatial concentration and functional diversification within China's AI labor market. On the one hand, advanced AI capabilities remain heavily concentrated within a small group of metropolitan innovation centers. On the other hand, AI-related labor demand has gradually diffused across a wider range of cities and application domains, indicating broader participation in the digital economy. These dynamics suggest

that digital inclusion in the AI era should not be understood solely in terms of access to core AI industries, but also in terms of the ability of cities to integrate AI technologies into locally relevant economic activities.

Several limitations should be noted. First, the analysis relies on online job advertisement data, which may not fully capture informal labor markets or all dimensions of realized employment demand. Second, the keyword-based identification of AI-related occupations may omit certain emerging skills or include occupations only partially related to AI technologies. Third, the analysis is primarily descriptive and does not attempt to establish causal mechanisms underlying the observed spatial patterns.

Future research could extend this framework by linking labor demand dynamics to firm-level innovation activity, university and research capacity, migration flows, or regional policy interventions. More broadly, the integration of high-dimensional labor market data with network and tensor-based methods offers a promising avenue for studying the evolving geography of technological change and digital inequality in both developing and advanced economies.

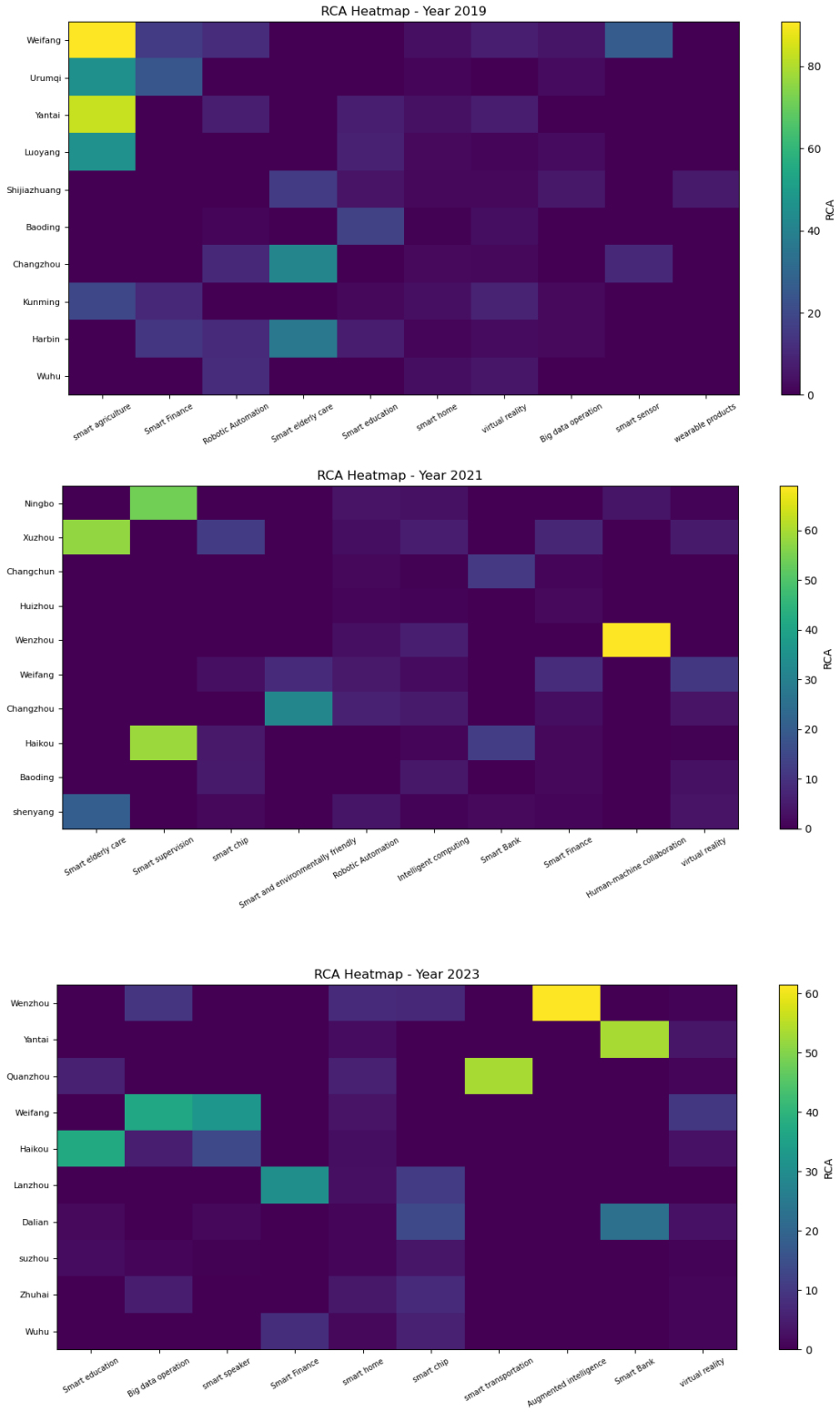

Fig. 4. Heatmaps of revealed comparative advantage across cities and AI skill categories in 2019 (top), 2021 (center), and 2023 (bottom).

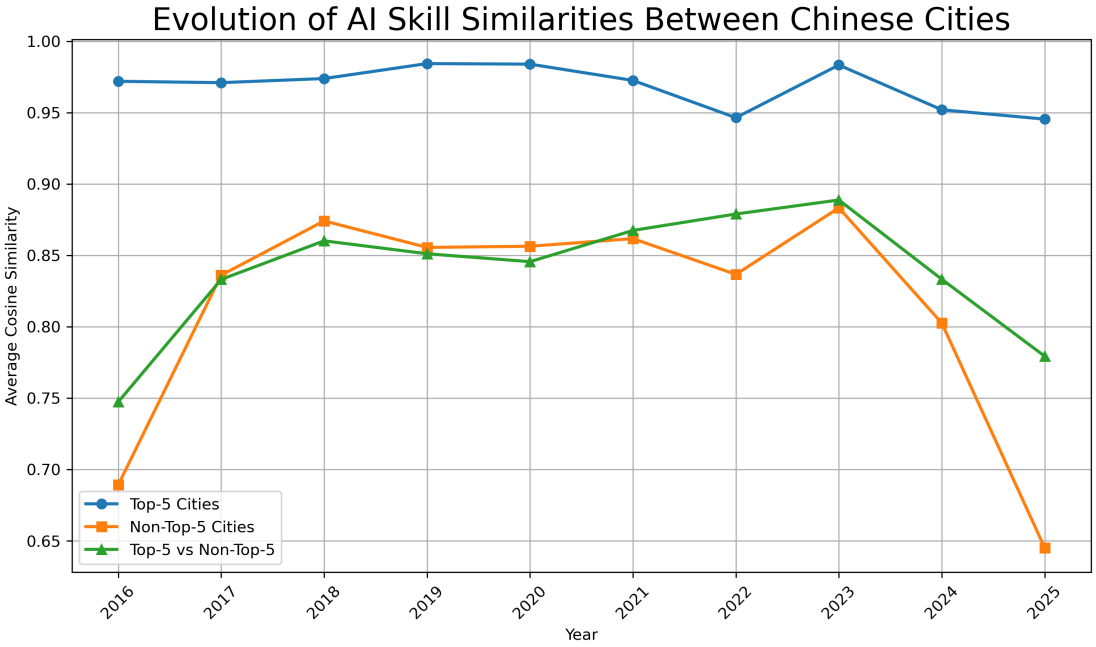

Fig. 5. Temporal trajectories of AI skill similarity across Chinese cities, 2016-2025.

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