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# AI fusion with traditional industries and urban development pathways: evidence from patent-based knowledge recombination in China

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**Abstract.** Artificial Intelligence (AI) is reshaping New Quality Productive Forces (NQPF) through cross-domain knowledge recombination. However, existing studies rely primarily on aggregate measures such as total factor productivity, limiting their ability to uncover the micro-level mechanisms through which AI drives productivity transformation. Drawing on Chinese patent data from 2000 to 2023 and the standardized technology codes of the International Patent Classification (IPC), this study develops an analytical framework grounded in knowledge recombination to characterize the breadth and depth of AI fusion with traditional industries. Using panel data on 49 Chinese cities and *K*-means clustering, this paper identifies three distinct development pathways: an "all-round leader" type, which leads across knowledge development, market application, and firm activity; a "market application" type, which advances AI commercialization rapidly on the strength of active firms and rich application scenarios; and a "university-driven" type, in which universities and research institutes dominate knowledge production. This study not only provides a novel measurement approach for capturing how AI reshapes NQPF but also offers an empirical foundation for formulating AI development strategies tailored to local conditions.

**Keywords:** artificial intelligence, knowledge recombination, patent analysis, urban development pathways

## 1. Introduction

Artificial Intelligence (AI) sits at the core of the ongoing technological revolution and is profoundly restructuring the global innovation system. By combining algorithms and data and by integrating knowledge across domains, AI transcends existing knowledge boundaries and gives rise to new technological paradigms and industries. This process captures the essence of New Quality Productive Forces (NQPF): unlike growth driven by increased inputs of traditional factors, NQPF arises from a step change in Total Factor Productivity (TFP) driven by technological innovation. How AI shapes NQPF has therefore become a question that warrants rigorous theoretical and empirical investigation.

Drawing on the standardized technology codes of the International Patent Classification (IPC), this paper measures the breadth and depth of AI fusion with traditional industries and, incorporating dimensions such as

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firm activity and market application, constructs a multidimensional measurement framework for AI-driven NQPF. A cluster analysis of 49 cities identifies three distinct development pathways. "All-round leader" cities leverage strengths in both basic research and industrial application to achieve knowledge recombination across the entire innovation chain; "market application" cities feature the rapid diffusion of AI into diverse traditional industries and its extensive deployment in application scenarios, reflecting a demand-pulled pattern of horizontal integration; and "university-driven" cities, anchored in universities and research institutes, specialize in frontier algorithm research, reflecting a pattern of vertical deepening grounded in upstream innovation. This typology not only reveals the multiple pathways through which AI shapes regional NQPF but also provides an actionable empirical basis for the policy of "developing NQPF according to local conditions".

## 2. Literature review

The conceptualization, models, and development pathways of NQPF have been extensively studied [1, 2]. This literature suggests that disruptive technologies such as Artificial Intelligence (AI) and quantum computing are key enablers of NQPF, and that the deep integration of AI with the real economy can drive sustained productivity transformation, yielding broad benefits for economic development, regional coordination, and industrial modernization [3, 4]. AI innovation can also translate into process innovation across an expanding range of sectors: as it combines with traditional industrial technologies, the resulting synergy triggers self-reinforcing effects within the technological system, accelerating its optimization and restructuring [5].

Because substantial TFP growth is a defining feature of NQPF, and because productivity growth captures the genuine, long-term economic effects of technological change [6], empirical research has focused on the relationship between AI and firm productivity. These studies find that AI adoption within firms optimizes factor allocation and reshapes value-creation models, thereby raising TFP [7]. Three findings are particularly salient in this literature. First, AI markedly stimulates firm innovation, especially process and product innovation: firm-level analyses show that AI-adopting firms are more likely to engage in Research and Development (R&D) and to restructure production processes more efficiently. Second, the productivity gains from AI are heterogeneous across firms, depending on firms' digital infrastructure, the technological intensity of their industries, and the regional innovation environment; they also hinge on the alignment between AI and firms' human capital, as the complementarity between AI and high-skilled labor is critical to realizing AI's productivity potential. Third, AI promotes TFP growth primarily by improving managerial decision-making, augmenting human capital, and accelerating knowledge spillovers [8-10]. Notwithstanding the short-run "productivity paradox" debate, the weight of long-run evidence supports a persistent positive effect of AI on TFP. However, because TFP is an aggregate measure, these studies capture the outcome of AI-driven transformation but not the underlying knowledge-recombination processes, nor how those processes differ across cities. It is precisely this gap that the present study addresses.

A subset of the literature examines the effects of AI on productivity and industrial structure from a regional economic perspective, revealing spatial heterogeneity in the underlying mechanisms. Using provincial panel data from China, Du et al. find significant regional differences in AI's effect on TFP: the effect is more pronounced in the eastern coastal region, which benefits from a stronger industrial base, more abundant human capital, and better infrastructure, whereas it is relatively weak in the central and western regions [11]. Drawing on AI patent data and city-level panel data, Chen and Cai find that although AI exerts a sustained positive effect on regional economic growth, its development patterns are isomorphic across regions and often misaligned with regional comparative advantages, thereby preventing the western region from fully capturing technological dividends [12]. Using provincial panel data, Hou and Song likewise find that AI promotes

dynamic convergence in the quality of regional economic growth—mainly by raising TFP and returns to capital—but that this convergence effect varies across regions [13]. Taken together, these studies indicate that AI's regional effects are positive on average but heterogeneous, depending on regional endowments, absorptive capacity, and market conditions.

Although existing studies have examined AI's impact on productivity and regional economic performance, rigorous empirical measurement of NQPF remains limited. NQPF rests on disruptive technologies that drive systemic transformation of the production function—a transformation reflected not only in efficiency gains but, more fundamentally, in the structural reconfiguration of knowledge systems and the broader reshaping of industrial ecosystems. Because such knowledge-level characteristics are difficult to observe directly, existing studies tend to quantify AI with aggregate counts or adoption measures, effectively treating it as a homogeneous, standardized input and thereby overlooking the heterogeneous patterns of knowledge recombination and AI fusion with traditional industries. As a result, this literature offers limited insight into the mechanisms and heterogeneous pathways through which AI drives NQPF. To address this gap, this paper adopts a knowledge-recombination perspective and incorporate the structure and evolution of AI technology itself into our analytical framework.

## 3. Data sources

The data used in this study comprise invention patent applications filed with the China National Intellectual Property Administration (CNIPA) between 2000 and 2023; each patent is assigned to its application year in the panel construction. The initial search returned 9,618,426 applications. To focus on innovation by domestic applicants, this paper screened the sample using applicant address information. First, this paper removed 2,878,326 applications whose applicant addresses were located outside China. Second, this paper excluded 96,428 records with duplicate application numbers, incomplete Chinese address information, or unidentifiable city affiliation. The final analytical sample comprises 6,643,672 Chinese invention patent applications.

Following WIPO recommendations[1], this paper extracted key fields from this sample (application number, IPC classification codes, title, and abstract) and applied a multistage screening procedure to identify AI-related patents. The procedure consists of three stages:

Stage 1: Identification based on the core IPC subclass. In line with OECD recommendations[2], this paper first labeled patents whose primary IPC subclass was G06N as "core AI patents", because WIPO designates G06N—covering machine learning, neural networks, and related areas—as the core classification for AI technologies.

Stage 2: Screening based on extended IPC classifications and keywords. To reduce omissions arising from reliance on the core subclass alone, this paper conducted a second-round screening of the patents not identified in Stage 1. Patents had to satisfy two criteria jointly: (1) the patent's primary IPC classification fell within one of the 17 extended AI-related IPC groups designated by WIPO (e.g., G06F15/18 and G10L15); and (2) after Chinese word segmentation with the open-source Jieba tokenizer, its title or abstract contained at least two distinct terms from a curated keyword list of 212 Chinese and English terms. The list consists mainly of Chinese terms (e.g., 机器学习 [machine learning], 神经网络 [neural network], and 深度学习 [deep

[1] WIPO. Patent Landscape Report: Generative Artificial Intelligence. Geneva: World Intellectual Property Organization. https://www.wipo.int/portal/en/index.html

[2] Identifying and measuring developments in artificial intelligence: Making the impossible possible. 2020.OECD Work paper.

learning]), supplemented with a small number of English strings (e.g., "AI" and "GPT") that frequently appear within Chinese patent text. Patents satisfying both criteria were classified as AI-application patents.

Stage 3: Supplementary identification based on keyword intensity. To further capture patents outside the AI core that nonetheless apply AI intensively, this paper applied text mining to the remaining sample. After synonym normalization of the keywords, a patent was likewise classified as an AI-application patent if normalized AI keywords appeared at least three times in total across its title and abstract.

In total, the three mutually exclusive stages identified 187,454 AI-related patents, accounting for 2.82% of the analytical sample. These patents comprise two categories: 108,849 core AI patents from Stage 1, which capture the development of core AI techniques, and 78,605 AI-application patents from Stages 2 and 3, which capture the application of AI technologies in specific domains (identified via extended AI-related classifications and keywords in Stage 2, and via keyword intensity in Stage 3). To assess the precision of the automated identification, this paper manually reviewed a random sample of 500 patents drawn from this set; 481 were confirmed as AI-related, a precision of 96.2/% and an implied false-positive rate of 3.8%. These results indicate that the automated procedure identifies AI-related patents with high precision.

# 4. Indicator design

Schumpeter famously characterized innovation as the "carrying out of new combinations" of existing means of production [14]—in essence, the recombination of existing technological components in new ways. Central to this definition is the recombination of different knowledge elements, which generates new interactions among technological components and gives rise to novel functions. Subsequent research has further established knowledge recombination as the primary source of technological novelty, conceptualizing innovation as adaptive search in a combinatorial possibility space [15].

Within this knowledge-recombination framework, each patent documents a discrete technological solution, and the IPC system provides a standardized taxonomy of the technological components such solutions combine (e.g., G06N for artificial intelligence and F03D for wind turbines). When an invention integrates knowledge elements from different technological fields, the patent is typically assigned multiple IPC codes [16]. For example, an invention for an intelligent wind-power control system may be classified under both F03D and G06N, indicating that it combines intelligent algorithms with wind-turbine technology and thus represents a cross-domain recombination of knowledge. Multiple classifications of a single patent therefore provide an observable manifestation of knowledge recombination at the patent level. Moreover, the unity-of-invention requirement stipulates that the components combined in a patent serve a single inventive concept, so the recombination recorded in patent documents reflects functionally coherent integration rather than arbitrary co-occurrence. Patents are thus a well-suited source of data for observing knowledge recombination.

## 4.1. Calculating knowledge distance

Step 1: Construction of the IPC co-occurrence matrix. This step quantifies the strength of association between technological fields in a global co-occurrence matrix. This paper first extracted the IPC codes assigned to each patent and mapped them to the most recent IPC revision at the four-digit subclass level—the same level used in Section 2—by means of the IPC version concordance tables published by WIPO [Version20240101]. For each patent, this paper then generated all unordered pairs of its distinct IPC subclasses and counted each pair once, recording the co-occurrence frequency $W_{ij}$ for every subclass pair $(i, j)$ across the entire dataset; this yields the global IPC co-occurrence matrix.

Step 2: Computation of PPMI embeddings. Raw co-occurrence counts confound the strength of association between two subclasses with their overall prevalence; this paper therefore convert the co-occurrence matrix into Positive Pointwise Mutual Information (PPMI) values, which discount such base-rate differences, [17] From the co-occurrence frequencies $W_{ij}$ (matrix $W$, symmetrized, diagonal set to zero), Equation (1) defines the joint and marginal probabilities:

$$P(i,j) = \frac{W_{ij}}{\sum_{a,b} W_{ab}}, P(i) = \frac{\sum_j W_{ij}}{\sum_{a,b} W_{ab}}, P(j) = \frac{\sum_i W_{ij}}{\sum_{a,b} W_{ab}} \quad (1)$$

Equation (2) then computes the $PPMI$:

$$PPMI(i,j) = max(0, log\frac{P(i,j)}{P(i)\,P(j)}) \quad (2)$$

Each subclass $i$ is represented by the $K$ dimensional vector of its $PPMI$ values with all other subclasses, as specified in Equation (3):

$$\widetilde{p}_i = [PPMI(i,1), \ldots..PPMI(i,K)] \quad (3)$$

where $K$ is the number of IPC subclasses ($K = 632$).

Step 3: Knowledge distance computation. In the embedding space, the knowledge distance between any two subclasses $i$ and $j$ is defined as the cosine distance (Equation (4)):

$$D_{ij} = 1 - \frac{V_i \cdot V_j}{\|V_i\| \, \|V_j\|} \quad (4)$$

where $V_i$ and $V_j$ are the embedding vectors of subclasses $i$ and $j$, respectively. shows that larger values of $\boldsymbol{D_{ij}}$ indicate that the two subclasses draw on more distant knowledge bases. Equation (4) shows that Cosine distances computed over $PPMI$ embeddings of co-occurring technology classes have been used in prior research to measure cross-domain recombination and technological novelty [18, 19].

## 4.2. Indicator system: a multidimensional measurement of AI-driven NQPF

Within the knowledge recombination framework, NQPF is not merely the accumulation of technologies. Rather, it involves AI acting as a general-purpose technology that structurally reconfigures existing production factors and technological systems, thereby generating new functions, new processes, and new industrial forms. To this end, this study constructs six indicators to characterize the knowledge recombination pathways through which AI drives urban NQP development.

### *4.2.1. AI–traditional industry fusion breadth (AI_fusion_breadth)*

NQPF depends on the broad penetration of AI into traditional industries and the systemic transformation it brings. Simple patent counts cannot distinguish "shallow application" from "deep restructuring". This paper therefore uses the knowledge distance defined in Equation (4) as a weight and compute the average knowledge distance across all AI-related patents in city *c*. The indicator is defined in Equation (5) as:

$$AI_Fusion_Breadth_{c,t} = \frac{1}{N_{c,t}} \sum_{p=1}^{N_{c,t}} \{ \frac{1}{|M_p|} \sum_{(i,j)\in M_p} D_{ij} \bullet \Pi(i \in AI, j \notin AI) \} \quad (5)$$

where $N_{c,t}$ is the number of AI-related patents in city *c* in year *t*; $M_p$ is the set of AI–non-AI subclass pairs in patent *p*; $D_{ij}$ is the knowledge distance between subclasses $i$ and $j$ defined in Equation (4); and $\Pi\,(i \in AI\ j \notin AI)$ is an indicator function that equals 1 when $i$ belongs to an AI subclass and $j$ belongs to a non-AI subclass, and 0 otherwise. Equation (5) therefore measures the extent to which AI-related patents in a city combine with traditional technology subclasses that have distant knowledge bases. A larger value indicates a broader AI–traditional industry fusion breadth.

**Table 1.** Calculation of AI–traditional industry fusion breadth

| Symbol | Meaning | Description |
|---|---|---|
| $c$ | City | The basic geographic unit of analysis, such as Beijing, Shanghai, and Shenzhen. |
| $t$ | Year | The year of patent application. |
| $i, j$ | IPC category | Two specific technological fields, such as G06N (neural networks) and G01S (radio navigation). |
| $N_{(ct)}$ | Number of AI patents | The number of AI-related patents in city $c$ in year $t$. |
| $M_p$ | Set of unordered IPC pairs | For example, if patent $p$ contains three IPC codes—G06N, G01S, and G06E—the number of unordered pairs is three. |
| $\Pi\{i \in \mathrm{AI}\, j \notin \mathrm{AI}\}$ | Indicator function | Equals 1 if $i$ belongs to a core AI IPC category (i.e., G06N) and $j$ does not; otherwise, it equals 0. |
| $D_{ij}$ | Knowledge distance | Cosine distance computed from PPMI + SVD embeddings (see above). |

The calculation process for this indicator is shown in Table 1. A higher value of this indicator indicates that a city's AI technologies are more frequently combined with traditional fields that are structurally distant in knowledge—such as agriculture, healthcare, and transportation. This reflects broader cross-domain recombination and thus expands the industrial application boundaries of NQPF.

*4.2.2. AI fusion depth (AI_fusion_depth)*

To measure the intensity of AI embeddedness in traditional industries, this paper constructs a city-level fusion depth indicator. This indicator is calculated as the weighted average of the product of penetration rate, growth momentum, and knowledge distance across all non-AI technological subfields related to AI in a given city-year, with each subfield's local patent stock serving as the weight (see Table 2 for details). A higher fusion depth indicates that AI not only penetrates traditional industries more broadly, but also achieves accelerating adoption and high-distance knowledge integration in key technological fields, thereby promoting intelligent production processes and TFP growth and forming the micro-level foundation of NQPF. The indicator is formally defined in Equation (6) as:

$$AI_Fusion_Depth_{c,t} = \frac{\sum_{s \in S_{c,t}} \left(\frac{AI_s}{Total_s} \times (\beta_s + \delta) \times \overline{D_{i,j}}\right) W_s}{\sum_{s \in S_{c,t}} W_s} \tag{6}$$

**Table 2.** AI integration depth calculation

| Symbol | Description |
|---|---|
| $S_{c,t}$ | The set of all non-AI IPC subclasses covered by AI patents in city $c$ in year $t$. |
| $AI_s$ | The number of AI patents in city $c$ in year $t$ that involve subclass $s$. |
| $Total_s$ | The total number of patents in city $c$ in year $t$ that involve subclass $s$. |
| $\beta_s$ | The slope of the three-year rolling AI penetration rate in city $c$; $\delta$ is a small positive constant ensuring non-negative weights. |

**Table 2.** Continued

| | |
|---|---|
| $\bar{D}_{i,j}$ | The average $D_{ij}$ across all AI patents involving subclass $s$. |
| $W_s$ | Weight, taken as the total number of patents in subclass $s$, reflecting the local importance of that technological field. |

*4.2.3. Knowledge Development Index (KDI)*

The Knowledge Development Index is measured as the share of basic AI patents filed by universities among all AI patents in each city. Universities are important sources of original innovation, and their level of participation is closely related to the knowledge depth of NQPF. A higher KDI indicates that a city relies more heavily on university-driven innovation in AI.

*4.2.4. Application Orientation Index (AOI)*

This index captures the extent to which a city's AI innovation is oriented toward application and is calculated as the proportion of applied AI patents in all AI patents. Patents classified under G06N are treated as representing basic AI technologies, such as neural networks and machine learning architectures, while all other AI-related patents are classified as applied. A higher AOI indicates that a city's AI activities are more focused on deployment in specific industrial scenarios rather than on general-purpose algorithm development, reflecting the "technology-enabled industry" application dimension of NQPF.

*4.2.5. Firm activity*

This indicator measures the participation of market actors in a city's AI innovation ecosystem. Its core component is the number of firms filing AI patents in a given city-year, which directly reflects the number of distinct firms engaged in AI R&D and application and provides a basic measure of innovation ecosystem diversity. A larger number indicates that a broader set of market actors is actively exploring AI technologies, thereby providing a diversified practical basis for NQPF. However, the firm count alone cannot fully capture the market structure of AI innovation. This paper therefore also compute a firm concentration index (HHI), defined as the sum of squared shares of AI patents across firms, as a complement to the core indicator. A higher HHI indicates that innovation activity is dominated by a few leading firms, whereas a lower value suggests a more dispersed and competitive landscape. In the subsequent cluster analysis, firm concentration is used as a validation indicator.

# 5. Path clustering of AI-driven NQP

To identify differentiated development patterns across Chinese cities in the process of AI-driven NQPF, this paper employs *K*-means clustering, an unsupervised learning method. This approach groups cities with similar multidimensional characteristics based on the intrinsic structure of the data, thereby identifying distinct city development types.

## 5.1. City sample selection

City sample selection follows explicit temporal and spatial criteria. The study period covers 2018–2023. This period is selected primarily because AI was elevated to a national strategic priority in 2017, after which a series of supporting policies were introduced. Since then, the industry has entered a new phase of rapid and regulated development. Analyzing data from this period therefore better reflects actual development dynamics under policy incentives.

As a data-driven method, cluster analysis requires input features with sufficient signal and discriminative power. To ensure the reliability of the clustering results, a minimum sample threshold should be set 20. If cities with very few AI patents were included, random fluctuations in a small number of patents could cause indicators such as fusion breadth and depth to vary sharply. This would make the clustering results unstable and obscure genuine structural patterns. AI patent data before 2018 are generally sparse and highly uneven across cities; many cities have too few patents to support robust cross-city comparison and pattern identification.

Accordingly, this paper apply an explicit quantitative criterion: only cities with an annual average of at least 100 AI-related patents over 2018–2023 are included. This yields a final sample of 49 representative cities with relatively active AI development, which form the core analytical sample.

## 5.2. Feature variables and data processing

The cluster analysis uses a five-dimensional feature vector for each city as input, constructed from the 2018–2023 averages of the five core indicators defined above (AI Fusion Breadth, Fusion Depth, Knowledge Development Index, Market Application Index, and Firm Activity). These indicators jointly characterize cities' AI-driven NQP patterns across four dimensions: knowledge supply, technology fusion, market application, and innovation actors.

The selection of five indicators follows a parsimonious approach to cluster analysis, avoiding the curse of dimensionality associated with high-dimensional spaces while ensuring clear interpretability of the results. This paper therefore examined potential multicollinearity among the indicators. As shown in Table 3, the Variance Inflation Factor (VIF) values range from 2.40 to 5.49. Although the VIF for Firm Activity (5.49) is somewhat above 5, all VIF values remain well below the conventional threshold of 10, and all tolerance values exceed 0.1. These results suggest that, although some correlation exists among the variables, multicollinearity is not a serious concern. Each indicator provides relatively independent information and is suitable for use in cluster analysis.

**Table 3.** Indicator independence test

| Indicator | VIF | Tolerance |
|---|---|---|
| Firm Activity | 5.49 | 0.18 |
| AI Fusion Breadth | 5.21 | 0.19 |
| Market Application Index | 4.59 | 0.22 |
| Knowledge Development Index | 3.09 | 0.32 |
| AI Fusion Depth | 2.40 | 0.42 |

Note: Source: Calculated by the authors.

Prior to analysis, this paper applied *Z*-score standardization to all variables to eliminate scale effects across indicators. This paper then repeated the above collinearity diagnostics on the standardized data to confirm that the feature vectors are suitable for cluster analysis.

## 5.3. City clustering results

To identify typical patterns of AI-driven urban NQP, this paper first determined the optimal number of clusters ($K$). This paper used the elbow method and the silhouette coefficient, both of which indicate that $K = 3$ is optimal: the elbow curve shows a clear inflection point at this value, and the silhouette coefficient reaches its

maximum. This suggests that the three-cluster solution achieves the best balance between within-cluster compactness and between-cluster separation.

To assess the robustness of the results, this paper conducted two validation exercises. First, this paper calculated silhouette coefficients and Calinski–Harabasz indices for $K = 2$ to $K = 5$, with both metrics peaking at $K = 3$. Second, to evaluate the sensitivity of the clustering results to algorithm initialization, this paper ran the $K$-means algorithm 100 times with random initializations; the average consistency of cluster assignments across runs was 0.91, indicating highly stable results. The final city clustering results are shown in Figure 1. Each axis represents a core indicator, with standardized values ranging from 0 to 1; a larger polygon area indicates that the city type performs more strongly on that indicator dimension.

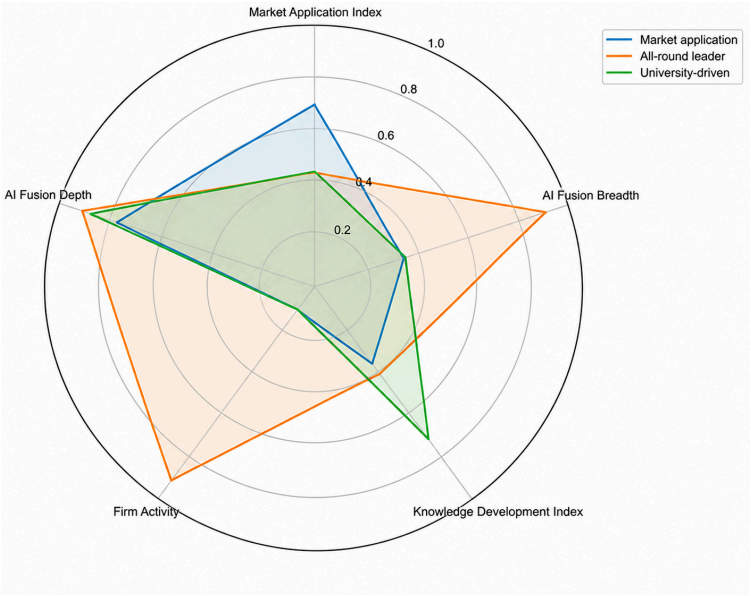



**Figure 1.** City clustering of AI shaping new quality productive forces

## 6. Research findings

Based on panel data from 49 cities during 2018–2023, this paper use $K$-means clustering to identify three typical patterns of AI-driven NQPF, which this paper label as the "all-round leader", "market application", and "university-driven" types. The clustering results yield six all-round leader cities (orange): Beijing, Shanghai, Shenzhen, Hangzhou, Guangzhou, and Nanjing; 13 market application cities (blue), represented by Suzhou, Dongguan, Foshan, and Ningbo; and 30 university-driven cities (green), represented primarily by Xi'an, Harbin, Lanzhou, Chengdu, and Wuhan. As shown in the radar chart, the three city types exhibit distinct configurations in the five-dimensional feature space, reflecting structural differences in the allocation of innovation factors and in the underlying development drivers.

### 6.1. All-round leader cities

Six cities—Beijing, Shanghai, Shenzhen, Hangzhou, Guangzhou, and Nanjing—fall into this category. In the radar chart, these cities exhibit relatively balanced and generally leading performance across all five dimensions: the Knowledge Development Index (KDI), the Market Application Index (AOI), AI fusion breadth, AI fusion depth, and firm activity, corresponding to the largest polygon area. Specifically, their KDI and AOI values are both high, indicating a strong linkage between knowledge creation and market application.

Their performance on AI fusion breadth and depth also exceeds that of the other two city types, reflecting both the broad reach and considerable depth of AI penetration in local industrial systems. In addition, high firm activity indicates that a diverse set of market actors participates in innovation activities. Overall, all-round leader cities demonstrate relatively comprehensive development across the main stages of the AI innovation chain and appear to be forming a self-reinforcing innovation cycle, representing the first tier of AI development among Chinese cities.

### 6.2. Market application cities

This pattern includes 13 cities, represented by Suzhou, Dongguan, Foshan, and Ningbo. In the radar chart, it exhibits a distinctive configuration with two prominent vertices, showing markedly higher scores on the Market Application Index (AOI) and firm activity than the other city types. This reflects a pronounced market-oriented development model, in which industrial demand and an active firm base serve as the primary drivers. However, these cities score relatively low on the Knowledge Development Index and show limited AI fusion depth, indicating constrained capacity for upstream knowledge supply and for addressing complex technologies, while their AI fusion breadth remains at an intermediate level. This driver structure suggests that the market application model excels at rapidly deploying and commercializing mature technologies, but remains relatively weak in indigenous innovation and deep technological integration, leaving the upstream end of the innovation chain underdeveloped.

### 6.3. University-driven cities

This type comprises thirty cities, including Xi'an, Harbin, Lanzhou, and Wuhan. Its radar chart shows a twin-peak profile that is the mirror image of the market-application pattern: the cities' strength is concentrated in the Knowledge Development Index, as reflected in the very high share of patents filed by universities and research institutes, and they also perform strongly in AI fusion depth. This advantage stems largely from the concentration of universities and research institutes in these cities, which endows them with strong knowledge-production capacity in basic research and selected technological fields. However, they score lowest of all city types on both the Market Application Index (AOI) and firm activity, producing two pronounced valleys that reveal a disconnect between academia and industry: AI knowledge generated locally has done little to stimulate application activity on the market side, and there is a shortage of firms capable of absorbing and commercializing technological outputs. Moreover, the breadth of their AI fusion remains limited. The core challenge for these cities is therefore to dismantle institutional barriers and translate their knowledge advantages into tangible industrial competitiveness and new momentum for economic growth.

## 7. Conclusion and research limitation

Existing research on NQPF has relied predominantly on Total Factor Productivity (TFP) as its measure. Although this approach facilitates econometric modeling, it offers limited insight into the micro-level mechanisms through which AI drives productivity transformation. NQPF is a multifaceted concept that encompasses not only incremental improvements in production efficiency but also the technological restructuring induced by innovation. To capture the dynamics of such restructuring, this paper draws on the International Patent Classification (IPC) to construct a set of multidimensional indicators that are both trackable and comparable. These indicators characterize the breadth and depth of AI fusion with traditional industries. More importantly, they make it possible to track how AI penetrates different domains over time—

which technological fields are the first to achieve deep integration with AI, and which remain at an early stage of contact or are untouched altogether.

The main contributions of this paper are as follows.

(1) At the methodological level, this paper draw on an IPC co-occurrence network to measure knowledge distance, which this paper then use to construct two core indicators: AI fusion breadth and AI fusion depth. These indicators capture not only the scope of AI penetration into traditional industries such as agriculture, manufacturing, healthcare, and transportation, but also the intensity of AI's embeddedness and the knowledge span involved in specific technological subdomains. They thus move beyond surface-level analyses based on simple patent counts or TFP regressions, revealing how AI generates new functions, processes, and business forms through cross-domain knowledge recombination.

(2) At the empirical level, a cluster analysis of 49 cities identifies three distinct development pathways: an all-round leader type, a market application type, and a university-driven type. This typology not only confirms that the policy of "developing NQPF according to local conditions" has a solid micro-level foundation, but also provides a reference framework for local governments when formulating AI development strategies.

(3) At the theoretical level, by focusing on the breadth and depth of AI fusion with traditional industries, this paper construct an NQPF measurement framework grounded in knowledge recombination. This framework preserves the innovation-driven essence of NQPF while rendering the concept decomposable at the level of individual technological fields and amenable to policy intervention, offering operational quantitative indicators for future theoretical modeling and empirical testing.

Admittedly, this study has several limitations, which in turn point to directions for future research.

(1) The analysis relies primarily on patent data to identify AI-related innovation activities. While this data source offers objectivity, it inevitably overlooks AI applications that substantially improve work efficiency yet fall outside the patent system. Such "non-patented" applications cannot be incorporated into our indicator system, even though they arguably constitute an important component of NQPF.

(2) A second limitation concerns sample representativeness. To ensure that the indicators are measured reliably, this paper focus on the 49 cities that averaged at least 100 AI patents annually over 2018–2023. These cities mainly occupy the "first tier" and "active tier" of AI development in China. However, cities whose annual AI patent counts fall below this threshold but that possess distinctive application scenarios are excluded from the analytical framework, and their development pathways remain unexamined. This is both a limitation of the present study and a promising avenue for future research.

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