The Dilemma of Fitness of Higher Vocational Education Specialty Settings and Regional Industrial Structure and the Path of Governance: An Empirical Study Based on Beijing Municipality

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Abstract. The precision of alignment between vocational education output and industrial needs is an important driver of regional economic development and a benchmark for modernized governance. In this paper we apply computational social science methods using big data analytics, machine learning and agent-based modeling to investigate the structural fitness between specialty offerings in Beijing HVE institutions and its emerging innovation-driven economy. We propose and implement a computational 3D diagnostic model (Deviation-Duplication-Aggregation) to evaluate 894 specialty offering points. Our multi-method analysis revealed a persistent "macro-convergence but micro-imbalance" paradox. While aggregate specialty distribution mirrors Beijing's service-dominated GDP, severe mismatch exists: critical undersupply for strategic high-precision and future industries and large oversupply and homogenization in saturated service majors. These mismatches are due to systemic failures in information flow, resource allocation, and collaboration incentives. We constructed a closed-loop smart governance framework centered on an AI-augmented data platform for precision navigation, supported by institutionalized multi-stakeholder synergy, strategic differentiation guided by institutional typologies, and dynamic evaluation-accountability system. This paper shows how computational methods and intelligent systems can be used to diagnose complex policy challenges and design proactive evidence-based governance mechanisms for education-industry co-evolution.

Keywords: Higher vocational education, specialty setting, industrial structure, collaborative governance, data-driven decision making, computational social science, AI in education, predictive analytics, smart governance

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1 Introduction

1.1 Background and Significance

Vocational education is the best route for cultivating technical and skilled talent essential for industrial innovation and economic competitiveness. A dynamic alignment between vocational education outputs and the regional industrial structure is therefore a key indicator of whether education governance is effective and modern.In China, this is a national policy, as the National Implementation Plan for Vocational Education Reform calls for an education system responsive to technological advances and changing market demands.

Beijing, the national capital and global innovation hub, is transitioning to a service-oriented, knowledge-intensive economy. With a GDP composition of 0.3% primary, 15.9% secondary and 83.9% tertiary sectors, its focus is on high-precision industries (e.g. artificial intelligence, integrated circuits, biopharmaceuticals) and future industries (e.g. quantum information, satellite internet) as outlined in "Digital China". This evolution creates unprecedented demand for new high-level technical and composite skills, posing a formidable challenge for the local HVE system to remain relevant and proactive.

1.2 Research Objectives and Contributions

This paper aims to assess the fitness of specialty settings in Beijing HVE institutions with the current and projected needs of the regional industrial structure. We compare 894 major deployment points of 25 institutions in 2023 with traditional sectors and strategically defined high-precision and future sectors.

The study makes three core contributions:

- Empirical & Methodological Contribution: Provides a comprehensive, multi-dimensional diagnosis using a novel 3D computational model, enhanced by cluster and regression analysis, to move beyond descriptive matching to explanatory typology building.
- Theoretical Contribution: Introduces and operationalizes a "smart collaborative governance" framework for HVE, which integrates classic collaborative governance principles with data-driven, AI-enhanced decision-support systems.
- Practical & Technological Contribution: Identifies specific actionable structural imbalances and proposes a technology-enabled governance pathway that can be transferred. This is a transferable blueprint showing the role of computational tools, from NLP for skill extraction to agent-based simulation for policy testing, in modernizing education governance.

2 Literature Review

2.1 International Governance Models and Practices

The global challenge of aligning vocational education with industry has led to the development of a number of governance models:

- Dual System Models (e.g. Germany, Switzerland): Deep, institutionalized enterprise involvement in curriculum design, delivery and assessment, directly embedding industry standards into national qualifications [1].
- Data-Driven Adaptive Governance (e.g. U.S. O*NET, Singapore SkillsFuture): leverage large-scale labor market analytics, real-time dashboards, and predictive modeling to forecast skill demands and enable agile, evidence-based adaptation of training programs [2]–[4]. These models are facilitated by advances in big data processing, machine learning algorithms and interactive data visualization.
- Technology-Enhanced and Transnational Collaboration: Involve developing "portable skills packages" for global value chains, immersive AR/VR simulation training, and require complex governance systems among international stakeholders [5], [6]. These models collectively reframe vocational education as a dynamic system embedded in larger ecosystems of industry, data and global networked governance.

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2.2 Domestic Research Context in China

Domestic research has established the "industry-employment-education" link as a fundamental analytical framework [7], [8]. Studies often use synergy theory and quantitative measures such as structural deviation coefficients to evaluate equilibrium. One common finding is the "double negative deviation": talent shortages in modernized primary industries and oversupply in some saturated secondary industries [9], [10]. Regional studies often attribute mismatches to local factors such as industrial attractiveness, institutional strategies and rigid funding models [11], while policy recommendations focus on administrative tools such as enrollment guidance and specialty cluster programs [12]. Significant research gaps include lack of dynamic forecasting models, lack of computational social science methods for system analysis, and limited research on how digital platforms can redesign collaborative governance processes [3], [5].

2.3 Theoretical Lens: Towards Smart Collaborative Governance

We rely on collaborative governance theory (cooperation of stakeholders) for attaining public goals otherwise impossible [13]. Trust, shared goals, dialogue, transparency are key principles for multi-actor systems such as HVE. We extend this theory by arguing that in the digital age effective collaboration is increasingly mediated and enhanced by shared data platforms and intelligent analytical tools. These technologies can build trust through transparency, provide a common factual basis for dialogue and allow precise accountability coordination. Our proposed framework represents an application of this "smart collaborative governance" concept to the domain of specialty setting.

3 Research Design and Methodology

3.1 Data Sources and Collection

A sequential mixed-methods design was employed:

- Industrial Demand Data: Macro-data on GDP, output, and employment for the three traditional sectors (2022) came from the Beijing Statistical Yearbook 2023. Definitions and targets for high-precision and future industries were sourced from official municipal plans, primarily the "Beijing Municipal 14th Five-Year Plan for High-Quality Development of Manufacturing and Digital Economy" (2021-2025) and the "Beijing Action Plan for Cultivating and Expanding Future Industries" (2023).To capture near-term dynamics, we also integrated a snapshot of online job postings (Q1 2022 – Q4 2023) from major Chinese recruitment platforms (e.g., Zhaopin, 51job) for Beijing, focusing on positions requiring HVE-level qualifications. To integrate industrial and educational classifications, a mapping protocol was developed by a panel of three domain experts, which aligns the National Standard Industrial Classification with the HVE Specialty Catalog based on primary occupational outputs.
- Educational Supply Data: Granular data on all 894 specialty offering points across 25 Beijing HVE institutions for the academic year 2023/2024 (including major names, disciplinary categories, enrollments) were collected from official disclosures.
- Qualitative Data: Semi-structured interviews were conducted with 15 key informants (administrators, officials, industry HR managers) selected purposively by sampling to understand governance barriers.In order to identify skill gaps, we examined publicly available aggregate graduate employment quality reports (2022-2023) published by Beijing HVE institutions on employment rates and starting salaries of strategic versus traditional majors.

3.2 Analytical Framework: The Computational 3D Diagnostic Model

The core analytical innovation is a 3D model deconstructing "fitness":

1) Deviation Dimension(D_i): Measures supply-demand balance. $D_i>0$ indicates oversupply; $D_i < 0$ indicates undersupply.

$$D_i = (S_i/S_{total})/(E_i/E_{total}) - 1 \tag{1}$$

where S_i is specialty offering share and $E_i$is economic weight (employment share used for sectoral balance, planned output share for strategic sectors). Fitness levels: High

($|D_i| < 1$), Medium ($1 \leq |D_i| < 3$), Low ($|D_i| \geq 3$).Conceptually, D_i represents a normalized ratio difference like a simple sector-specific divergence measure. If this is not equivalent to Kullback-Leibler divergence measure (differentiation between two probability distributions), D_i identifies the proportional difference between supply (specialty share) and demand (economic weight) for each sector i.

2) Duplication Dimension (Concentration Index C):Measures institutional homogenization. Lower Cindicates higher duplication.

$$C = (\Sigma_{j=1}^{k} P_j)/P_{total} \tag{2}$$

where P_j is offering points for major j. The Herfindahl-Hirschman Index (HHI) was also computed for robustness.This index is the concentration of offerings across institutions. Low C means many institutions offer the same few majors which indicates homogenization. It could be seen as a macro-level indicator related to the cosine similarity between individual vectors of the curriculum. High duplication (low C) indicates high average pairwise cosine similarity between institutions.

3) Aggregation Dimension (Aggregation Index A): Measures institutional focus/niching. Higher A indicates offerings concentrated in fewer disciplinary categories.

$$A = N_{types}/N_{categories} \tag{3}$$

where N_{types} is unique majors and $N_{categories}$ is disciplinary categories spanned.

Figure 1 illustrates the conceptual framework of the Smart Collaborative Governance model for HVE specialty setting, integrating the 3D diagnostic model with the four-pillar intervention framework.

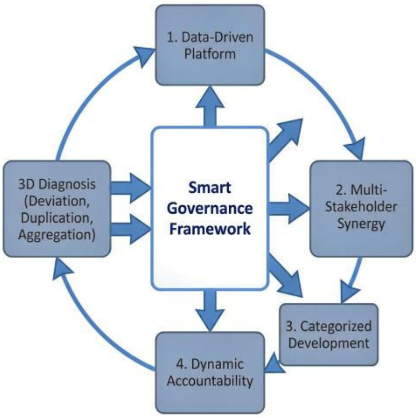

Fig. 1. Conceptual Framework of the Smart Collaborative Governance Model for HVE Specialty Setting.

3.3 Advanced Analytical Procedure

Quantitative analysis was conducted using Python (Pandas, NumPy, SciPy) and R.

- Cluster Analysis: K-means clustering was applied to institution-level vectors of standardized (D, 1/C, A) values. The K-means algorithm was chosen for its efficiency and interpretability in partitioning medium-sized datasets into distinct groups. The optimal number of clusters (k=3) was determined using the elbow method and silhouette analysis. This identified distinct institutional typologies.
- Regression Analysis: Ordinary Least Squares (OLS) regression explored associations. Dependent variables included an institution's D_i for high-precision sectors and its A index. Independent variables included a binary indicator for a formal industry advisory board, per-student funding, and institution type.
- Predictive Simulation: A proof-of-concept agent-based model (ABM) was developed in NetLogo to simulate system dynamics. The main agents are HVE institutions. Decision rules are simplified to simulate real-world behavior: they see demand signals (modeled as projected employment growth rates for different major categories from historical and plan data) and policy incentives (e.g., increased per-student funding or subsidies for opening majors in strategic sectors). Institutions open new majors or phase out existing majors based on perceived demand strength and available incentives, but also based on risk-aversion factor favoring duplicating popular existing majors. Firms and students are modelled as aggregate demand signals and not individual agents in this prototype. This ABM allows exploration of long-term fitness trends under different policy scenarios (e.g., with or without targeted subsidies).
- Data Visualization & Qualitative Analysis: Tableau and Matplotlib/Seaborn were used for dashboards and heat maps. Interview data were coded in NVivo and triangulated with quantitative findings.

4 Empirical Findings and Analysis

4.1 Beijing's Industrial Structure

Beijing's economy is decisively tertiary and innovation-focused (Table 1). Strategic plans target high-precision and future industries as primary growth engines, demanding advanced technical skills.

Table 1. Beijing's Three-Sector Industrial Structure (2022)

Sector	**GDP Share (%)**	**Employment Share (%)**	**Implied Demand Trend**
Primary	0.3	2.2	Contracting
Secondary	15.9	16.4	Stable, upgrading
Tertiary	83.9	81.4	Expanding, specializing

4.2 Deep-Dive Analysis of HVE Specialties

Structural Mismatch.

Macro-distribution shows convergence (80.3% of offerings in tertiary sector), but granular analysis reveals severe imbalance within the tertiary sector (Table 2). High-precision industries face a critical talent supply gap $D_i = -6.90$. This undersupply is supported by the labor market signals: we analysed online job postings (2022-2023), and found postings for technical positions AI, integrated circuits, and biopharma grew over 35% year-on-year while the supply of relevant HVE graduates remained flat. Furthermore, available graduate outcome data shows a significant wage premium (approximately 25-40% higher starting salaries) for graduates employed in these strategic sectors than graduates employed in traditional service sectors, indicating both demand urgency and the economic incentive for better alignment.

Table 2. Fitness Within the Tertiary Sector

Category	Program Share (%)	Est. Economic Weight (%)	D_i	Implication
Traditional Services	39.51	33.3	+0.19	Balanced/Slight Surplus
High-Precision Industries	35.60	42.5	-6.90	Critical Undersupply
Future Industries	5.20	8.1	-2.90	Significant Gap
Other Services	19.69	16.1	+0.22	Balanced

Homogenization and Strategic Diffusion.

High market saturation is evident (Table 3). "Big Data & Accounting" is offered by 59.4% of institutions, exemplifying "label inflation" where emerging tech terms are appended to traditional curricula without deep alignment with strategic sector needs.

Table 3. Highly Duplicated Majors (2023)

Major Name	Institutions Offering	Offering Rate (%)
Big Data & Accounting	19	59.38
E-Commerce	14	43.75
Preschool Education	14	43.75
Computer Application Technology	14	43.75

Major Name	Institutions Offering	Offering Rate (%)
Artificial Intelligence Technology Application	12	37.50
Big Data Technology	11	34.38
Computer Network Technology	10	31.25
Digital Media Art Design	10	31.25

Institutional Typology from 3D Analysis.
Cluster analysis based on (D, C, A) profiles revealed three institutional types:

- Type A: Generalized Followers (n=22): High duplication ($C < 0.15$), low aggregation ($A < 2.5$), moderate negative deviation. Characterized by chasing enrollment in popular, established majors.
- Type B: Specialized Partners (n=7): Lower duplication, higher aggregation ($A > 3.0$), closer alignment with strategic sector demand. Typically have long-standing, deep industry partnerships.
- Type C: Misfitted (n=3): Exhibit high positive deviation in declining sectors (e.g., primary industry majors), representing the most severe strategic misalignment.

Preliminary regression showed that a formal industry advisory board was positively related to a higher aggregation index A ($\beta = 0.42$, $p = 0.08$), suggesting a mechanism by which structured collaboration can lead to specialization. This result is not surprising considering the small sample size and limited significance of governance design.

5 Discussion: From Diagnosis to a Smart Governance Pathway

5.1 Systemic Roots of Imbalance

The paradox stems from collaborative governance failures:

- Information Failure:Lack of real-time labor market intelligence creates 2-3 year adaptation delay.
- Resources Failure: Low-risk funding and low-risk approval reward duplication over innovation.
- Collaborative Architecture Failure: Absence of structured platforms for co-decision-making leads to superficial partnerships.

5.2 A Four-Pillar Smart Collaborative Governance Framework

Figure 1 illustrates the integrated framework. The 3D diagnosis directly informs targeted interventions within a closed-loop system. The proposed framework combines strengths of international models: the structured industry involvement of German Dual System, the data-driven agility of Singapore SkillsFuture, and the technology-enhanced collaboration of transnational training projects. Beijing's fast industrial upgrading and concentrated innovation environment calls for a unique “smart” approach using digital tools.

Pillar 1: Data-Driven Precision Navigation

- Action: Deploy a Beijing Industrial Talent Intelligence Platform integrating job postings, patents, and economic data. Implement AI modules: NLP for real-time skill extraction from job descriptions; LSTM or Transformer-based models for demand forecasting; and interactive, API-enabled dashboards.
- Governance logic: Creates a shared, objective knowledge base—the "technological backbone" for trust and evidence-based action.

Pillar 2: Multi-Stakeholder Synergy with Digital Tools

- Action: Establish digital "Power-Responsibility-Benefit (PRB) Agreements" and Industry-Education Co-Management Committees with shared digital workspaces for curriculum co-design, resource pledging, and progress tracking.
- Governance logic: Digitally formalizes roles and processes, making collaboration transparent, accountable, and efficient.

Pillar 3: Categorized Development Informed by Typology

- Action: Guide institutions based on their cluster type. Support Type B (Specialized Partners) to build "world-class specialty clusters." Guide Type A (Generalized Followers) through platform analytics to consolidate into 2-3 strategic niches. Mandate transformation for Type C (Misfitted). This push has to be balanced with safeguarding education diversity and access.A broad approach is needed: resources should be directed towards STEM and digital majors, but support should be maintained for high quality non-STEM non-STEM pathways (e.g. premium services, cultural heritage, green trades) that meet specific needs and offer viable careers in regions with regional importance (e.g., premium services, cultural heritage, green trades).This is strategic priority, not wholesale marginalization.
- Governance logic: Replaces one-size-fits-all policy with differentiated, data-informed strategies to build a complementary ecosystem.

Pillar 4: Dynamic Accountability with Continuous Monitoring

- Action: Reform evaluation using KPIs like "strategic industry alignment rate" and "industry co-investment depth." Embed these into a "Diagnosis-Monitoring-Adjustment-Funding" cycle powered by the platform, with real-time KPI dashboards for all stakeholders.

- Governance Logic: Closes the loop, fostering a culture of continuous learning and mutual accountability sustained by technology.

5.3 Implementation Considerations

Translating this framework into practice requires a phased and pragmatic approach. Key steps include:

- Pilot testing: Launch limited scale pilot of HVE institutions with 3-4 HVE institutions and 2 industry clusters to test platform, PRB agreement and new KPIs based on lessons learned.
- Stakeholder engagement and capacity building: Conduct workshops and trainings for institution leaders, faculty and industry partners to ensure acceptance and build digital literacy for using new tools.
- Data privacy and security: Develop and enforce strict protocols for data collection, anonymization, sharing and usage of the platform based on relevant regulations (e.g., China Data Security Law).
- Iterative scaling: After pilot evaluation, gradually extend framework to more institutions and sectors, adapt governance mechanisms to regional contexts in Beijing.

6 Conclusion, Limitations, and Future Research

6.1 Conclusion

This study diagnoses the "macro-convergence, micro-imbalance" paradox in Beijing's HVE system through a computational social science lens. The roots are systemic, lying in a governance model ill-adapted for dynamism and complexity. We propose a smart collaborative governance framework as the necessary paradigm shift. By placing an AI-augmented data platform at its core, this framework enables precision navigation, catalyzes structured collaboration, facilitates strategic differentiation, and ensures transparent accountability. Implementation would position HVE not as a passive follower, but as an active co-creator shaping regional industrial upgrading. The study provides a transferable blueprint underscoring the indispensable role of computational methods and intelligent systems in solving complex socio-technical policy challenges.

6.2 Policy Implications

- Invest in Shared Data Infrastructure: Prioritize the Beijing Industrial Talent Intelligence Platform as a public good.
- Incentive Differentiation: align funding and accreditation mechanisms with the institutional typologies (A, B, C) to reward specialization and punish misalignment.
- Designate Cooperation: Establish digital PRB agreements and co-management committees for key strategic industries.

- Pilot the framework: Implement a phased pilot as outlined in the implementation considerations, focusing on a subset of institutions and strategic sectors to de-risk the process and generate evidence for scaling.

6.3 Limitations and Avenues for Future Research

- Study Design: The cross-sectional analysis warrants future longitudinal tracking. The small-N regression results are indicative, not definitive.
- Model Development: The 3D model and ABM prototype require further validation. A promising avenue is developing a full-scale system dynamics model, calibrated with time-series data, to simulate policy impacts and optimize the governance framework.
- Data Integration: Future work should incorporate real-time data from online labor platforms and enterprise systems.
- Generalizability: Applying and adapting this framework in regions with different industrial bases (e.g., manufacturing hubs) is a critical next step for establishing its broader utility.Additionally, future research should explicitly model and evaluate the potential long-term impacts of strategic steering on educational diversity, student choice, and social equity.

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