ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Research on Skilled Talents Co-construction and Sharing in Guangdong-HongKong-Macao Greater Bay Area

Xueyu Chen[1,*]

[1] Guangzhou Engineering & Technical Vocational College, Guangzhou, Guangdong, China

SUMMARY: *Industrial upgrading and regional coordination in the Guangdong-Hong Kong-Macao Greater Bay Area have accelerated, and the demand for cross-regional training, mobility and sharing of skilled personnel has continued to grow. In this paper, a computational research framework integrating multi-source heterogeneous data processing, knowledge graph modeling, collaborative network representation, spatio-temporal prediction and strategy recommendation is constructed for the joint construction and sharing scenario of skilled talents in the Bay Area, and a unified analysis of training collaboration, evaluation mutual recognition, employment and entrepreneurship, public services, industrial chain matching and open configuration is carried out. The experimental data covers January 2020 to December 2024, a total of 14,728 original samples are collected, and 13,860 are retained after cleaning. The results show that the comprehensive recognition scores of Shenzhen and Guangzhou are 0.912 and 0.901 respectively, the strength of Guangzhou-Shenzhen relationship is 0.91, the open configuration efficiency is improved from 0.62 to 0.86 under the comprehensive optimization scenario, the model prediction accuracy is 91.8%, RMSE and MAE are 0.052 and 0.039, respectively. The research shows that data fusion, graph relationship modeling and spatio-temporal prediction coupling can effectively improve the refined analysis ability of the co-construction and sharing research of skilled talents in the Bay Area, which is of practical significance for promoting regional collaborative governance and the construction of high-level skilled talents system.*

KEYWORDS: *Guangdong-hong Kong-Macao Greater Bay Area; Co-construction and sharing of skills and talents; Knowledge graph; Spatio-temporal prediction*

1 Introduction

The Guangdong-Hong Kong-Macao Greater Bay Area is an important region with a high degree of openness, perfect industrial system and intensive innovation resources. The coordinated development of advanced manufacturing, modern service industry and digital economy puts forward higher requirements for the training, flow and allocation of high-quality and skilled talents [1]. With the deepening of regional coordination, the joint construction and sharing of skilled talents is no longer limited to the talent supply problem within a single city, a single college or a single enterprise, but has gradually evolved into a systematic issue that penetrates multiple links such as education and training, evaluation and identification, employment services, industrial coordination and open development [1]. At present, the work of skilled talents in the Bay Area is accelerating to the direction of collaborative learning and training, integration of incentive and evaluation, localization of employment and entrepreneurship, and

*jyzhang6@126.com
https://doi.org/10.65102/is2026318 Published: 30 April, 2026

homogenization of public services. At the same time, the construction of modern industrial colleges, the collaborative cultivation of key industrial chains, and the platform support of serving Chinese enterprises to go global are also becoming an important starting point for the co-construction and sharing of skilled talents [2, 3].

However, from the perspective of actual operation, the joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area still faces prominent structural constraints. On the one hand, a large number of heterogeneous data have been accumulated among government departments, vocational colleges, trade associations, industrial parks, employment enterprises, training platforms and public service institutions, which have obvious differences in caliber, granularity, timeliness and standards, making cross-regional comparison and overall analysis more difficult [4]. On the other hand, there are differences in the pace of policy support, skill certification, job demand, service supply and industry acceptance in different cities, which makes the flow and allocation of skilled talents often show problems such as information lag, insufficient coordination and imprecise matching. Especially under the background of modern industrial upgrading, the demand for skilled talents has formed a close coupling relationship with the evolution of the industrial chain, the change of the post ability structure and the regional open layout. It is difficult to effectively reveal the dynamic mechanism and potential law of the co-construction and sharing of skilled talents in the Bay Area by simply relying on traditional statistical analysis and empirical judgment [5, 6].

At the same time, the development of data intelligence technology provides new method support for the research of such complex problems. Multi-source heterogeneous data processing can improve the integration efficiency of scattered information; knowledge graph can depict the correlation structure between government, colleges, enterprises, industrial chains and service platforms; collaborative network analysis can identify key nodes and relationship strength; spatio-temporal prediction model can help grasp the flow of skills and talents, changes in supply and demand, and the evolution trend of policy effects [7-9]. The introduction of these calculation methods into the research on the joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area not only helps to improve the technical content of the research, but also can transform the issues that originally focus on experience summary into analysis objects that can be characterized, calculated, predicted and optimized. In this way, whether the coordination of skilled personnel training is effective, whether the mutual recognition of evaluation is smooth, whether the public service is balanced, and whether the key industrial chain is matched with the skilled personnel chain can be identified and evaluated more finely under a unified data framework [10].

Based on this, this paper builds a computational research framework for multi-source data fusion, relational graph modeling and spatio-temporal evolution analysis based on the practical needs of the co-construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area, combined with key scenarios such as regional education and training, industrial collaboration, public services and open development. The focus of this research is to identify the core subject and collaborative relationship in the co-construction and sharing of skills and talents by uniformly characterizing the relevant data of skills and talents in the Bay Area. Through network modeling and dynamic analysis, the coupling characteristics between learning and training, evaluation and incentive, employment and entrepreneurship and public services are revealed. The talent allocation effect and regional coordination level under different strategies are evaluated by prediction and simulation mechanism. This paper hopes to promote the extension of skilled talents research to digitalization, modeling and intelligence at the methodological level, and provide technical support and decision-making reference for the construction of a higher-level collaborative development system of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area.

2 Computational modeling method of skills co-construction and sharing in Guangdong-Hong Kong-Macao Greater Bay Area

2.1 Problem description and overall computing framework for the co-construction and sharing of skilled talents in the Bay Area

The Guangdong-Hong Kong-Macao Greater Bay Area is a regional coordination system covering education and training, skills evaluation, job matching, employment and entrepreneurship, public services and open configuration. The system also involves government departments, vocational colleges, technical colleges, enterprises, industrial parks, trade associations, modern industrial colleges and integrated service platforms and other subjects. There are significant differences in resource supply, demand response and coordination rules between different subjects. Based on this, this paper constructs an overall computing framework from four levels of data integration, relationship modeling, effectiveness evaluation and dynamic prediction, and strives to identify the core elements, subject relationships and evolution trends of the co-construction and sharing of skilled talents in a unified analysis space.

In terms of state description, the comprehensive state of the Bay Area skill talent co-construction and sharing system at time t is expressed as follows:

$$X_t = [P_t, R_t, J_t, S_t, I_t, O_t] \tag{1}$$

Here,P_t represents the learning and training collaboration feature, R_t represents the incentive evaluation feature, J_t represents the employment and entrepreneurship feature, S_t represents the public service feature, I_t represents the industrial chain collaboration feature, and O_t represents the open configuration feature.

Since the original data come from multiple sources such as policy texts, training programs, colleges and majors, job requirements, certificate information, public service records and talent flow records, and the indicator dimensions and value ranges are quite different, all kinds of observed variables are normalized first. Let the original index be $x_{t,m}$, then its standardized result is as follows:

$$z_{t,m} = \frac{x_{t,m} - \min(x_m)}{\max(x_m) - \min(x_m)} \tag{2}$$

where, m denotes the MTH observation index. In the relationship modeling layer, the main bodies such as government, colleges, enterprises, industrial platforms and service bases are abstracted as nodes, and the training cooperation, job transportation, evaluation mutual recognition, service linkage and project collaboration are abstracted as edges. The strength of collaborative relationship between node i and node j is defined as follows:

$$a_{ij} = \sigma(h_i^{\top} Q h_j + \lambda r_{ij}) \tag{3}$$

where h_i and h_j denote the node representation vector, Q is the relational mapping matrix, r_{ij} is the realistic collaboration record, λ is the regulation coefficient, and $\sigma(\cdot)$ is the activation function, respectively. This formula not only considers the similarity degree of the subjects in the feature space, but also considers the support effect of realistic collaborative behavior, so it can more accurately reflect the real correlation strength between the subjects in the co-construction and sharing of skilled talents in the Bay Area.

At the overall evaluation level, the comprehensive efficiency index of co-construction and sharing of skilled talents in the Bay Area is defined as follows:

$$Y_t = \omega_1 T_t + \omega_2 E_t + \omega_3 L_t + \omega_4 C_t + \omega_5 M_t + \omega_6 O_t \tag{4}$$

Among them, T_t is the training coordination degree, E_t is the evaluation integration level, L_t is the employment and entrepreneurship undertaking ability, Ct is the public service balance degree, Mt is the matching degree of the industrial chain, Ot is the open configuration ability, and it meets $\sum_{k=1}^{6} \omega_k = 1$.

In order to make the model take into account feature representation, relationship characterization and prediction accuracy at the same time, the overall optimization objective is set as follows:

$$\mathcal{L} = \alpha\mathcal{L}_{fuse} + \beta\mathcal{L}_{graph} + \gamma\mathcal{L}_{pred} + \eta\|\Theta\|_2^2 \tag{5}$$

Here, $\mathcal{L}_{fuse}$ represents the data fusion error, $\mathcal{L}_{graph}$ represents the relationship modeling error, $\mathcal{L}_{pred}$ represents the prediction error, $\|\Theta\|_2^2$ is the regularization term, α,β,γ,η are the balance coefficients. Through this objective function, coordination constraints can be established among multi-source data integration, subject relationship identification and sharing efficiency prediction, making the overall framework both interpretable and computable. The overall computational framework is shown in Figure 1.

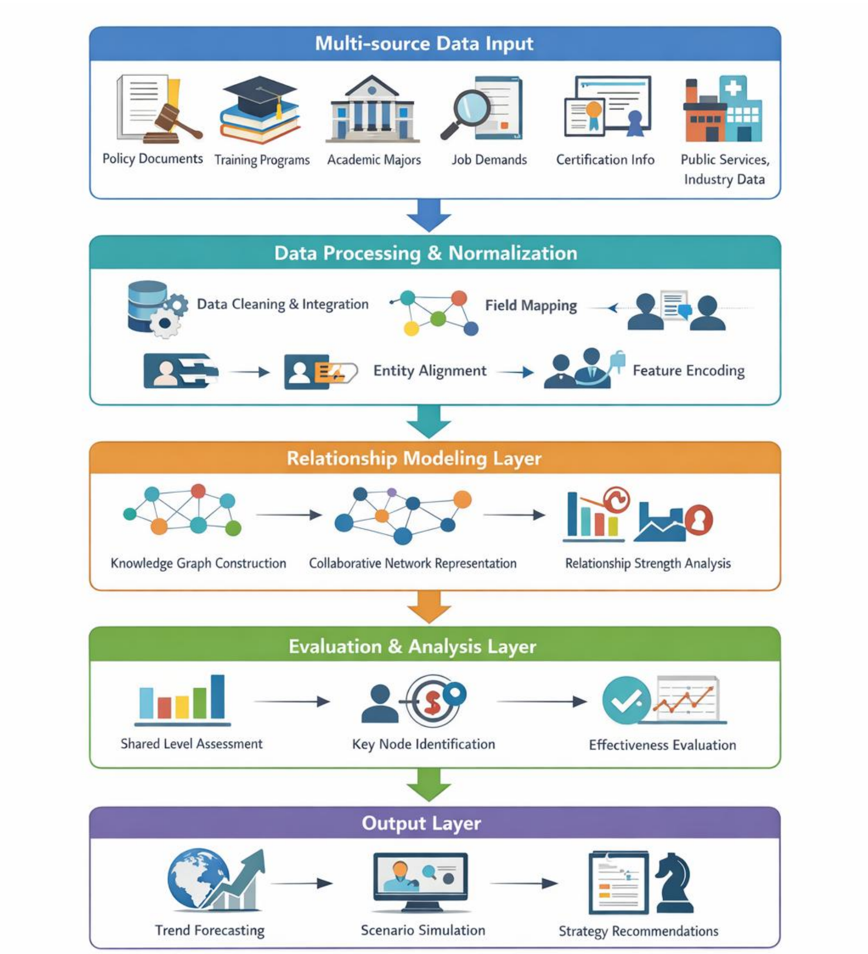

Figure 1: Diagram of the overall computational framework

Figure 1 shows that the research on the co-construction and sharing of skilled talents in the Bay Area can be carried out along the path of "data aggregation, standardized processing, relationship modeling, effectiveness evaluation and strategy output", so as to integrate dispersed talents, positions, services and industrial information into a unified calculation and analysis process. Table 1 shows the definition of core elements for the co-construction and sharing of skills and talents in the Bay Area.

Table 1: Definition table of core elements for co-construction and sharing of skilled talents in the Bay Area

Definition of Core Shared Elements	Main Meaning	Typical Observed Variables	Modeling Objective
Learning and Training Collaboration	The level of collaboration in training resources and talent cultivation platforms across regions	Number of joint training programs, number of shared courses, co-construction rate of practical training bases	Measure training linkage capability
Incentive and Evaluation Integration	The degree of alignment among skill certification, competition incentives, and evaluation rules	Certificate mutual recognition rate, standard consistency, conversion rate of competition achievements	Measure rule coordination level
Localization of Employment and Entrepreneurship	The regional capacity to absorb skilled talents and support entrepreneurship	Local employment rate, job matching rate, intensity of entrepreneurship support	Measure absorption capability
Homogenization of Public Services	The accessibility and balance of public services across regions	Service coverage rate, processing timeliness, cross-city service availability rate	Measure service balance level
Industrial Chain Collaboration	The degree of alignment between the skilled talent chain and key industrial chains	Talent gap in key industries, major-job relevance rate, participation rate of modern industrial colleges	Measure industrial matching degree
Open Allocation Capability	The level of support for cross-border cooperation and enterprises going global	Number of international training programs, carrying capacity of service bases, overseas project talent demand	Measure openness support capability

Table 1 shows that the joint construction and sharing of skilled talents in the Bay Area is a composite system composed of training coordination, evaluation connection, employment acceptance, service balance, industrial adaptation and open support, which also provides a clear basis for subsequent sub-module modeling and result analysis.

2.2 Multi-source heterogeneous skilled talents data collection and cross-regional standardized processing methods

The computational analysis of the joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area first depends on whether the data base is complete, whether the caliber is unified, and whether the cross-regional mapping is stable.

Because the information related to skills and talents in the Bay Area is distributed in different scenarios such as policy documents, colleges and training platforms, enterprise recruitment systems, vocational qualification and competition databases, employment and entrepreneurship service platforms, public service platforms, industrial chain collaboration platforms and open cooperation service bases, the data structure includes texts, tables, record flows and relationship links at the same time. Semantically, it involves talents, posts, certificates, courses, institutions, industry nodes and services and other entities. Without unified collection and standardization, the subsequent relationship modeling is prone to field conflicts, entity ambiguities and regional caliber offset. Based on this, this paper constructs the collection, cleaning, mapping, alignment and output process for multi-source heterogeneous skilled talent data to ensure the basic stability of input data in integrity, consistency and computability.

Let the multi-source data set of skilled talents in the Bay Area be:

$$D = \bigcup_{k=1}^{K} D_k, D_k = \{r_1^{(k)}, r_2^{(k)}, \dots, r_{n_k}^{(k)}\} \tag{6}$$

Here, D_k is the KTH data source, k is the total number of data source categories. This definition integrates data scattered in different platforms and departments into the same collection space, which provides the basis for subsequent field mapping and entity fusion. For each record, this paper retains five kinds of basic information, such as subject identification, timestamp, region identification, business category and attribute field, so as to complete the unified index in cross-region scenarios.

Considering the absence and redundancy of multi-source records, the information integrity of a single record is defined as follows:

$$\chi_i = \frac{1}{M}\sum_{j=1}^{M} 1\,(x_{ij} \neq \emptyset) \tag{7}$$

where M is the total number of fields, $1(\cdot)$ is the indicative function, and x_{ij} is the JTH field value of record i. This index is used to measure the information retention degree of the sample before standardization. When the completeness is too low, the corresponding records will enter the completion, merging or elimination process to reduce the error accumulation caused by missing propagation.

Since different data sources have naming differences and field differences for the same concept, this paper sets up a unified field mapping function:

$$\tilde{x}_{ij} = g_j(x_{ij}, \pi_k) \tag{8}$$

where π_k represents the original field template of the KTH data source, $g_j(\cdot)$ represents the mapping rule of the JTH target field, and $\tilde{x}_{ij}$ is the standard field value after mapping. Through this process, different expressions such as "skill level", "qualification level", "certificate category", "training project name" and "employment destination" can be unified into the preset dictionary, so as to reduce the semantic deviation when cross-platform data splicing.

In the entity alignment phase, in order to solve the homonym and heteronym problems, the matching similarity between entity a and entity b is defined as follows:

$$s(a, b) = \theta_1 s_{name} + \theta_2 s_{type} + \theta_3 s_{region} + \theta_4 s_{time} \tag{9}$$

Here, s_{name} is the name similarity, stype is the category agreement, s_{region} is the region agreement, s_{time} is the temporal proximity, and $\theta_1 + \theta_2 + \theta_3 + \theta_4 = 1$. When s(a,b) exceeds the threshold, the two entities are considered as the same object and merged. In order to comprehensively evaluate the effect of standardization processing, the cross-regional data consistency index is defined as follows:

$$Q=\beta_1\bar{\chi}+\beta_2\bar{s}-\beta_3\delta \tag{10}$$

which the $\bar{\chi}$ for average integrity, $\bar{s}$ aligned for average similarity, the delta as the repeat rate, β_1,β_2,β_3 for weight coefficient. The higher the Q value, the more suitable the data quality is to enter the subsequent knowledge graph construction and collaborative network analysis stage. Therefore, this paper forms a standardized processing path of "multi-source acquisition - cleaning and duplication removal - field mapping - entity alignment - region calibration - structured output".

Figure 2 shows the process of multi-source heterogeneous data acquisition and standardization.

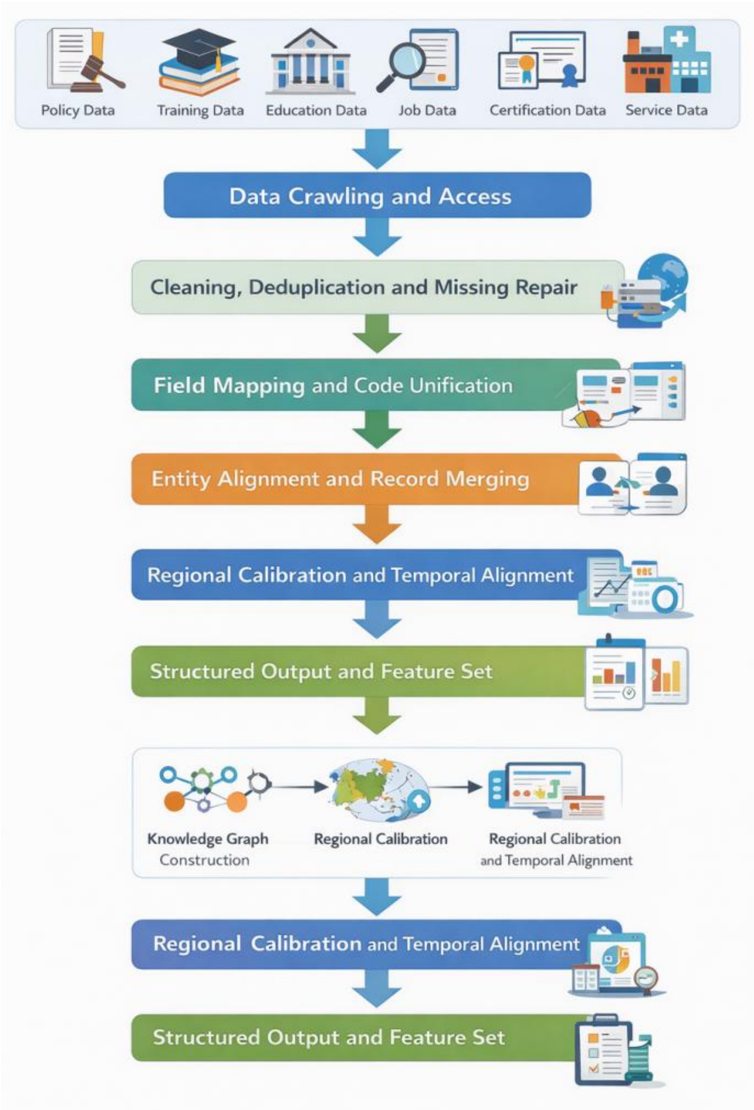

Figure 2: Flowchart of multi-source heterogeneous data acquisition and standardization

Figure 2 shows that the data processing of skilled talents in the Bay Area is not a simple process of data cleaning, but a continuous transformation process from original collection to semantic unification, and then to structured output, in which field mapping, entity alignment and region alignment are the key links that determine the subsequent modeling effect. The data sources and field descriptions are shown in Table 2.

Table 2: Data source and field description table

Data Carrier	Main Fields	Time Range	Main Purpose
Policy and Institutional Data	Issuing institution, release date, policy theme, target beneficiaries, measure type	Continuous samples from recent years	Extract policy coordination features
Institutional and Training Data	Institution name, specialty direction, course name, training level, base type	Academic years and project cycles	Describe training supply capacity
Enterprise Position Data	Enterprise name, job title, skill requirements, salary range, affiliated industry	Monthly or quarterly	Characterize industrial demand structure
Qualification Evaluation Data	Certificate type, skill level, evaluation institution, competition category, conversion result	Annual continuous samples	Analyze the level of evaluation alignment
Employment and Entrepreneurship Data	Employment destination, regional flow direction, entrepreneurship type, support amount, retention status	Monthly or annual	Measure absorption and mobility characteristics
Public Service Data	Service category, processing timeliness, platform traffic, frequency of cross-regional service processing, satisfaction level	Monthly continuous samples	Evaluate the degree of service balance
Industrial Chain Collaboration Data	Industrial node, cooperating institution, project name, job vacancy gap, corresponding specialty	Project cycle	Analyze industrial chain matching relationships
Open Cooperation Data	Base name, project type, target region, talent demand, service scale	Annual continuous samples	Evaluate open allocation capability

2.3 Modeling and sharing network representation of skilled talents collaborative relationship based on knowledge graph

After the completion of multi-source data collection, field mapping and entity alignment, the research on the co-construction and sharing of skilled talents in the Bay Area needs to further answer two key questions: one is the relationship between different subjects to form collaborative interaction, and the other is what kind of network structure this interaction shows at the regional level. Only relying on ordinary table data or single-dimensional statistical indicators, it is often only possible to see the changes in the number of jobs, training times or certificate scale, but it is difficult to reveal the deep relationship between the government, colleges, enterprises, industrial parks, public service platforms, modern industrial colleges and open service bases. Therefore, this paper introduces the knowledge graph method to organize the subjects, resources, activities and results in the skilled talents co-construction and sharing scenario into a structured relationship network. On this basis, a sharing network representation model is constructed to describe the transmission path between training collaboration, evaluation mutual recognition, job matching, service linkage and open configuration.

The knowledge map of skills and talents in the Bay Area is set as follows:

$$G = (h, r, t, \tau, \ell) \tag{11}$$

Here, h represents the head entity, r represents the relation type, t represents the tail entity, τ represents the time token, and ℓ represents the region token. Compared with the ordinary triple, this paper introduces two additional dimensions of time and region, which can simultaneously describe the dynamic relationships such as "a college carries out joint training with an enterprise in a certain year", "a city implements mutual recognition of a certain type of certificate", and "a service platform provides skills support for enterprises in a certain region".

In terms of entity construction, this paper divides the nodes in the knowledge graph into seven categories, including government agencies, education and training subjects, enterprise subjects, talent subjects, industrial chain nodes, service platforms and open cooperation carriers. Let the attribute set of entity vi be A_i, the context set be C_i, and the region label be L_i. Then the initial representation of the node is defined as follows:

$$e_i = \phi(A_i \| C_i \| L_i) \tag{12}$$

Here, $\phi(\cdot)$ denotes the embedding mapping function and $\|$ denotes the concatenation operation. The representation not only preserves the basic attributes of entities, but also incorporates regional features and context information into the embedding space, so as to enhance the comparability between similar entities in different regions. For example, although an industrial college in Guangzhou and an industrial college in Shenzhen belong to different cities, they may have strong similarities in professional structures, cooperative enterprise types and project organization methods, and this similarity can be expressed through unified embedding.

In terms of relationship modeling, this paper focuses on identifying six types of core relationships, namely, training cooperation relationship, evaluation mutual recognition relationship, job delivery relationship, entrepreneurial support relationship, public service relationship and open collaboration relationship. For any relation triple, the semantic consistency score is defined as follows:

$$f_r(h, t) = \|e_h + r - e_t\|_2^2 \tag{13}$$

Here, e_h and e_t are the vector representations of head and tail entities, respectively, and r is the relation vector. If a triple has strong rationality in the semantic space, its score should be lower. This formula can be used to determine whether a training program truly connects a college and an enterprise "and whether a mutual recognition mechanism truly connects the skill evaluation system of the two places", so as to improve the accuracy of relationship recognition.

Considering that the co-construction and sharing of skilled talents in the Bay Area is not driven by a single relationship, but a composite network formed by the interweaving of multiple relationships, this paper further defines the comprehensive sharing strength between subjects as follows:

$$w_{ij} = \ln\left(1 + \rho_1 n_{ij}^{(p)} + \rho_2 n_{ij}^{(c)} + \rho_3 n_{ij}^{(j)} + \rho_4 n_{ij}^{(s)} + \rho_5 n_{ij}^{(o)}\right) \tag{14}$$

Among them, $n_{ij}^{(p)}$ represents the training cooperation frequency between subject *i* and subject *j*, $n_{ij}^{(c)}$ represents the number of evaluation and identification collaboration, $n_{ij}^{(j)}$ represents the number of post matching and transportation, $n_{ij}^{(s)}$ represents the number of public service linkage, $n_{ij}^{(o)}$ represents the number of open cooperation project collaboration, and ρ_1~ρ_5 is the relationship weight. After logarithmic transformation, the extreme high-frequency values can be compressed while preserving the strong relationship differences, avoiding excessive pulling of the whole network caused by a few highly connected subjects.

In order to describe the structural positions of different agents in the shared network, the collaborative importance of node i is defined as follows:

$$C_i = \lambda_1 \frac{d_i}{\sum_j d_j} + \lambda_2 \frac{b_i}{\max(b)} + \lambda_3 \frac{m_i}{\max(m)} \tag{15}$$

Here, d_i is the node degree, b_i is the mediator index, m_i is the number of connections across regions, and $\lambda_1+\lambda_2+\lambda_3=1$. This index comprehensively considers the connection breadth, bridging ability and cross-regional radiation ability of nodes, and can be used to identify key hubs in the Bay Area skill sharing network. For example, some leading enterprises may have a high degree of connection in job absorption, while some vocational colleges or service platforms have a stronger bridging role in cross-city collaboration. The importance of the two types of main bodies is not the same, and they need to be distinguished by comprehensive indicators.

In the shared network representation layer, the inter-regional collaboration matrix is further constructed as follows:

$$M_{ab} = \frac{1}{|V_a||V_b|} \sum_{i \in V_a} \sum_{j \in V_b} w_{ij} \tag{16}$$

Among them, V_a and V_b represent the subject set of region a and region b respectively, and M_{ab} represents the average synergy strength of the two places in the co-construction and sharing of skills and talents. Through the construction of matrix M, the relationship between micro subjects can be elevated to the network analysis at the regional level, so as to observe the structural differences between different combinations such as Guangzhou - Shenzhen, Shenzhen - Hong Kong, Zhuhai - Macao in terms of training linkage, evaluation mutual recognition, job acceptance and service cohesion. This promotion from entity relationships to regional networks makes the subsequent sharing level measurement and spatio-temporal evolution prediction have a clearer structural foundation.Figure 3 shows the schematic diagram of the knowledge graph and sharing network construction of skilled talents.

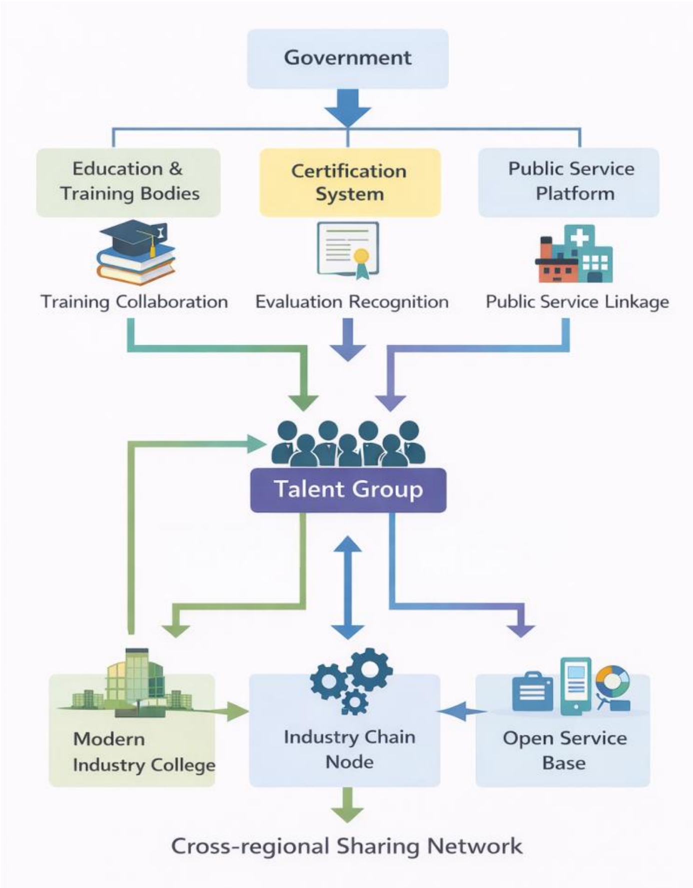

Figure 3: Schematic diagram of the knowledge graph and sharing network construction of skilled talents

Figure 3 shows that the knowledge graph of skills and talents in the Bay Area is not a simple entity summary, but a composite structure connected by multiple relationships such as training cooperation, evaluation mutual recognition, job matching, service linkage and open collaboration, with government, colleges, enterprises, talents, industrial chains and service platforms as core nodes. In this structure, the knowledge graph assumes the functions of entity recognition and relationship organization, and the sharing network is responsible for presenting the cross-subject and cross-region collaboration intensity and propagation path. The combination of the two can completely express the network pattern of co-construction and sharing of skills and talents in the Bay Area, and also provide a computational relationship basis for subsequent efficiency evaluation and spatio-temporal prediction.

2.4 Spatio-temporal prediction and strategy recommendation mechanism for effectiveness evaluation of co-construction and sharing

The joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area is not a static result, but a dynamic process that continues to change with the fluctuation of industrial demand, policy adjustment, platform linkage and cross-regional flow. Different cities have obvious differences in training supply, evaluation connection, job absorption, public service and open cooperation, and these differences will be continuously transmitted through industrial chain coordination, talent flow and service spilt. Therefore, it is difficult to reflect the inertial characteristics and future evolution direction of inter-regional collaborative relationships by only measuring the sharing level at a certain time point. In order to improve the predictability of the effectiveness evaluation of co-construction and sharing, based on the above multi-source data fusion and knowledge graph modeling, this paper introduces a spatio-temporal prediction and strategy recommendation mechanism, which integrates the trend change in the time dimension and the regional linkage in the spatial dimension into a unified framework, so as to realize the continuous prediction of sharing efficiency and the intelligent screening of optimization schemes.

Let the shared state matrix of each region in the bay area At time t be Z_t and the inter-region collaborative adjacency matrix be A_t, then the spatio-temporal fusion state can be defined as follows:

$$\mathrm{H_t} = \varphi(\mathrm{Z_t} + \mathrm{A_t Z_t} + \mathrm{H_{t-1}}) \tag{17}$$

where $\varphi(\cdot)$ represents the nonlinear mapping function, $\mathrm{A_t Z_t}$ is used to describe the spatial propagation effect of the regional cooperative network on the current state, and H_{t-1} represents the historical state at the last time. This equation can simultaneously preserve the local characteristics, neighborhood spillover effects and time inertia characteristics, so that the model can not only identify the sharing changes within a single city, but also reflect the collaborative diffusion process between Guangzhou, Shenzhen, Hong Kong, Macao and other nodes.

In the prediction layer, let the estimated value of sharing efficiency in the next Δ time steps be $\hat{y}_{t+\Delta}$, then:

$$\hat{y}_{t+\Delta} = \psi(\mathrm{H_t}, \mathrm{u_t}, \mathrm{q_t}) \tag{18}$$

Among them, u_t represents the policy disturbance term, which mainly describes the external shocks such as skill evaluation reform, joint training plan, platform co-construction and talent service optimization. qt represents the industrial demand disturbance term, which mainly reflects the factors such as the expansion of key industrial chains, the change of enterprise recruitment structure and the increase or decrease of open cooperation projects. Through Equation (18), the model can estimate the change direction and fluctuation range of the sharing level in the future while maintaining the historical continuity, so as to avoid relying only on static indicators for judgment.

Considering that the efficiency improvement of co-construction and sharing often requires the collaborative promotion of multiple strategies, this paper further sets up a scenario simulation module. If the variable increment vector corresponding to the KTH strategy scheme is $\Delta x(k)$, the comprehensive revenue brought by it is defined as follows:

$$\mathrm{U_k} = \sum_{h=1}^{H} \gamma^{h-1} \left(\hat{y}_{t+h}^{(k)} - \hat{y}_{t+h}^{(0)} \right) - \lambda c_k \tag{19}$$

Here, $\hat{y}_{t+h}^{(k)}$ represents the predicted sharing efficiency in period h after implementing strategy k, $\hat{y}_{t+h}^{(0)}$ represents the predicted value in the baseline scenario, c_k is the policy cost, γ is the time discount factor, and λ is the cost penalty coefficient. The implication of this equation is that different strategies should not only compare short-term improvements, but also measure the continuous benefits and implementation costs simultaneously. For example, cross-regional course sharing, certificate mutual recognition expansion, job collaborative release, service platform interconnection and open cooperation project expansion may improve the level of sharing, but the investment scale is not consistent with the effective cycle.

In the policy output layer, the policy combination with the maximum comprehensive revenue under the resource constraints is selected as the recommendation result, namely:

$$\Pi^* = \arg\max_{\Pi} \sum_{k\in\Pi} U_k \quad \text{s.t.} \sum_{k\in\Pi} c_k \le B \tag{20}$$

Here, Π represents the set of candidate policies and B is the resource budget upper bound. The optimization process can take policy support, training resources, public service capacity and industrial collaboration capacity into the decision-making scope at the same time, so as to make the recommendation results closer to the practical operation logic of the co-construction and sharing of skilled talents in the Bay Area. Figure 4 shows the spatio-temporal prediction and policy recommendation mechanism.

Figure 4: Spatio-temporal prediction and policy recommendation mechanism diagram

Figure 4 shows that spatio-temporal prediction and policy recommendation are continuous processes driven by historical data, supported by regional linkage, corrected by scenario simulation and finally output optimized paths. Through this mechanism, the research on the co-construction and sharing of skilled talents in the Bay Area can be further extended from the result description to the trend analysis and scheme generation, which provides a direct method support for the effectiveness measurement, evolution analysis and strategy simulation in the following chapter IV.

3 Experimental design and data preparation

3.1 Data source and preprocessing

The experimental data in this paper are constructed around the core scenario of the joint construction and sharing of skills and talents in the Guangdong-Hong Kong-Macao Greater Bay Area. The time range is set to January 2020 to December 2024, and the spatial scope covers 11 city nodes in the Bay Area. A total of 14728 original data were collected, including 328 policy and system data, 1462 college and training data, 6185 enterprise post data, 1274 qualification evaluation data, 1936 employment and entrepreneurship data, 1587 public service data, 1202 industrial chain collaboration data and 754 open cooperation data. In the structured processing, nearly 200 alliance member units, 19 professional committees, 84 innovation and entrepreneurship bases, 146 professional qualification recognition items, 189 social security service Windows, 70 government service entity Windows and more than 200 high-frequency service items were uniformly coded. A basic sample library for training collaboration, evaluation mutual recognition, post matching, service linkage and open configuration was formed.

After the original samples are collected, the format is unified, the primary key is removed, the outlier is removed and the field is cut, and then the organization name, job category, certificate level, industry label and regional code are standardized and mapped. After cleaning, a total of 13860 valid samples were retained, and the sample retention rate was 94.11%. Among them, the missing fields mainly focus on variables such as job segmentation requirements, entrepreneurial support methods and cross-regional service records. For the problem of local missing, this paper adopts the neighborhood weighted completion method, and the estimated value of the missing field xij is defined as follows:

$$\hat{x}_{ij} = \sum_{q \in \mathcal{N}(i)} \omega_{iq} x_{qj} \tag{21}$$

Here, $\mathcal{N}(i)$ represents the set of neighborhood samples similar to sample i, and ωiq is calculated as follows:

$$\omega_{iq} = \frac{\exp(-d_{iq})}{\sum_{p \in N(i)} \exp(-d_{ip})} \tag{22}$$

where, d_{iq} represents the distance between samples. For the time series modeling part, continuous observation segments are generated according to a fixed sliding window:

$$S_t = [X_{t-L+1}, X_{t-L+2}, \dots, X_t] \tag{23}$$

Here, L is the time window length. The final dataset was divided into training set, validation set and test set by 7:2:1, and the number of samples was 9702, 2772 and 1386, respectively. After the above processing, the experimental data are improved in terms of field consistency, time continuity and regional alignment, which can provide stable data support for subsequent sharing network construction, efficiency prediction and strategy recommendation.

3.2 Experimental environment and parameter setting

In order to ensure the stability of the model training and evaluation process, this paper completes the experiment in a unified software and hardware environment. The hardware platform uses Intel Xeon Silver 4314 processor with 2.40 GHz frequency, 64 GB memory, NVIDIA RTX 4090 graphics processor, 24 GB video memory, and 1 TB SSD storage device. The software environment is Ubuntu 22.04 64-bit operating system, programming language is Python 3.10, deep learning framework is PyTorch 2.1, and supporting CUDA 12.1 and cuDNN 8.9. Pandas, NumPy and Scikit-learn were combined to implement the data processing part, and NetworkX and graph learning tools were used to complete the knowledge graph and network computing module.

In terms of parameter Settings, the multi-source feature embedding dimension is set to 128, the relationship representation dimension is set to 64, the shared network modeling uses a 2-layer graph propagation structure, and the number of attention heads is set to 4. The time window length of the spatio-temporal prediction module is set to 6, the hidden layer dimension is set to 256, the Dropout is set to 0.2, and the batch size is set to 64. The optimizer uses AdamW with an initial learning rate set to 0.0005, weight decay coefficient set to 5×10^{-5}, training rounds set to 120, and an early stopping mechanism triggered when there is no improvement in the validation set for 10 consecutive rounds. To reduce the influence of random fluctuations, all experiments were repeated for 5 times, and the final results were averaged as the model performance output. Such an experimental environment and parameter combination can balance training efficiency, model convergence speed and result stability, and provide reliable support for subsequent effectiveness evaluation and strategy simulation.

4 Analysis of results

4.1 Analysis on identification results of basic characteristics of joint construction and sharing of skilled talents in the Bay Area

In order to identify the basic state of the joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area, this paper comprehensively measured the major cities in the Bay Area from the four dimensions of learning and training collaboration, evaluation connection, employment acceptance and service support, and formed the basic feature recognition results. On the whole, Guangzhou and Shenzhen are at the forefront of the comprehensive recognition score relying on strong industrial absorption ability, training resource gathering ability and platform linkage ability. Foshan and Dongguan maintained a high level by virtue of their manufacturing base and school-enterprise synergy advantages; Zhuhai, Hong Kong and Macao perform well in openness and collaboration and service facilitation, but there are still some differences in training scale and job undertaking intensity. Table 3 shows the recognition results of basic features for the co-construction and sharing of skilled talents in the Bay Area.

Table 3: Recognition results of basic characteristics of joint construction and sharing of skilled talents in the Bay Area

City	Number of Samples / Records	Training Collaboration Index	Evaluation Integration Index	Employment Absorption Index	Service Balance Index	Comprehensive Identification Score
Guangzhou	1624	0.893	0.876	0.918	0.901	0.901
Shenzhen	1748	0.905	0.884	0.926	0.933	0.912
Foshan	1386	0.852	0.831	0.861	0.840	0.846
Dongguan	1495	0.847	0.826	0.879	0.851	0.851
Zhuhai	1124	0.801	0.794	0.822	0.836	0.813
Hong Kong	1032	0.762	0.821	0.788	0.821	0.798
Macao	964	0.738	0.806	0.771	0.789	0.776

Table 3 shows that Shenzhen has the highest comprehensive recognition score (0.912), followed by Guangzhou (0.901). Foshan and Dongguan are 0.846 and 0.851 respectively, which are in the middle and upper level of the Bay Area. In contrast, the comprehensive recognition scores of Hong Kong and Macao are 0.798 and 0.776, respectively, which are 0.114 and 0.136 different from those of Shenzhen. This result shows that the co-construction and sharing of skills and talents in the Bay Area has formed an obvious core city leading pattern, but there is still room for further improvement of cross-regional training collaboration and public service balance.

4.2 Analysis of mining results of integration relationship between learning training collaboration and incentive evaluation

In the process of co-construction and sharing of skilled talents in the Bay Area, the integration of learning and training collaboration and incentive evaluation is not independent of each other, but a key mechanism that jointly acts on the quality of talent training, the efficiency of certificate circulation and the ability of job adaptation. Based on regional collaborative networks and evaluation mutual recognition records, this paper measured the training cooperation intensity, evaluation cohesion level and certificate mutual recognition correlation between Guangzhou, Shenzhen, Foshan, Dongguan, Zhuhai, Hong Kong and Macao. On the whole, the relationship strength between Guangzhou and Shenzhen, Shenzhen and Hong Kong, Zhuhai and Macao is relatively high, indicating that the core cities and cross-border nodes have stronger linkage ability in curriculum co-construction, project joint training, qualification linkage and service collaboration. Foshan, Dongguan, Guangzhou and Shenzhen are more reflected in the industrial support relationship between manufacturing skills training and job evaluation. Figure 5 shows the heat map of the integration relationship strength between learning and training collaboration and evaluation.

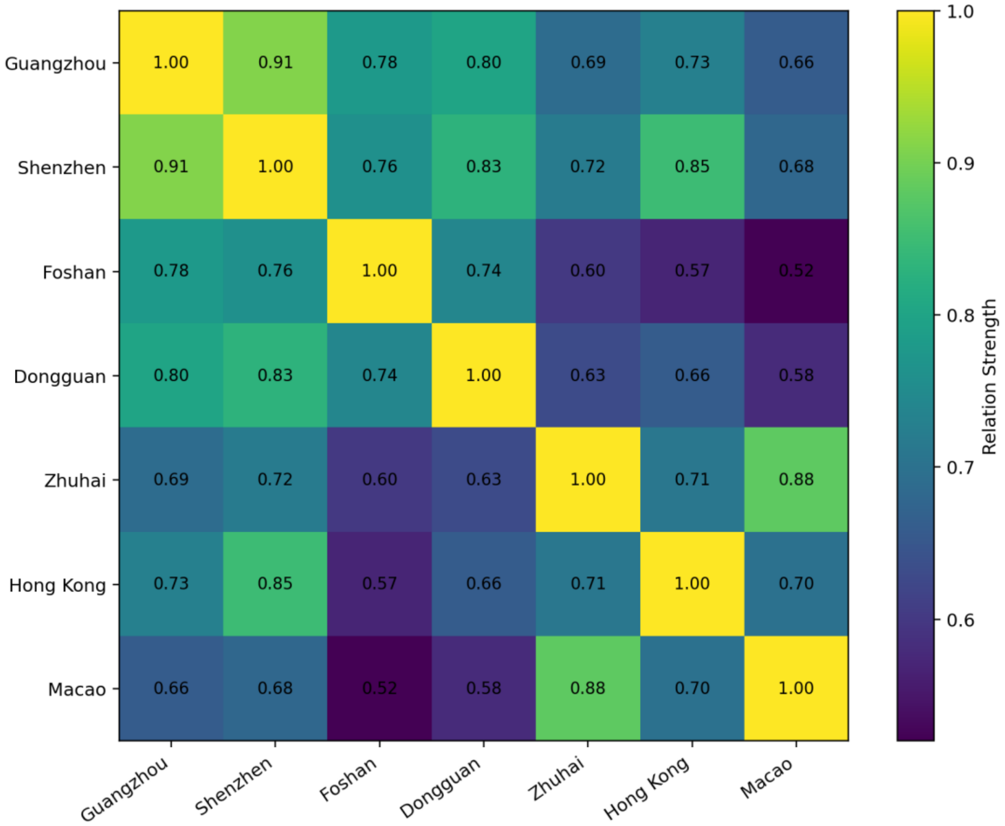

Figure 5: Strength of Training Collaboration and Evaluation Integration

As can be seen from Figure 5, the relationship strength between Guangzhou and Shenzhen reaches 0.91, between Shenzhen and Hong Kong reaches 0.85, and between Zhuhai and Macao reaches 0.88, which is significantly higher than 0.52 between Foshan and Macao and 0.58 between Dongguan and Macao. This indicates that a collaborative pattern has been formed within the Bay Area with Guangzhou and Shenzhen as the core and Zhuhai-Macao and Shenzhen-Hong Kong as the cross-border fulminations. The distribution characteristics of learning and training collaboration and mutual recognition of evaluation in different cities are decreasing from the center to the periphery. Table 4 shows the statistics of key relationships between learning and training synergy and mutual recognition of evaluation.

Table 4: Statistical table of key relationships between learning and training collaboration and mutual recognition of evaluation

Regional Pair	Number of Joint Training Programs / Items	Number of Shared Courses / Courses	Certificate Mutual Recognition Rate / %	Evaluation Alignment Index	Comprehensive Relationship Strength
Guangzhou–Shenzhen	48	126	89.4	0.903	0.91
Shenzhen–Hong Kong	37	98	86.7	0.872	0.85
Zhuhai–Macao	29	74	84.9	0.861	0.88
Guangzhou–Foshan	34	81	78.6	0.794	0.78
Shenzhen–Dongguan	31	76	80.8	0.817	0.83
Foshan–Dongguan	22	58	73.2	0.748	0.74

Table 4 further shows that the number of joint training projects between Guangzhou and Shenzhen reaches 48, the number of shared courses reaches 126, and the mutual recognition rate of certificates is 89.4%, which is the highest level among all regional combinations. Although the project size of Zhuhai-Macao is slightly smaller, the comprehensive relationship strength reaches 0.88, indicating that the cross-border evaluation connection efficiency is high. In contrast, the mutual recognition rate between Foshan and Dongguan is 73.2%, which is 16.2 percentage points lower than that between Guangzhou and Shenzhen. In general, the integration of learning and training collaboration and incentive evaluation in the Bay Area has shown an obvious gradient structure, and the combination of strong relationships is mainly concentrated between Guangzhou and Shenzhen, Shenzhen and Hong Kong, and Zhuhai-Macao, which provides a direct basis for the subsequent promotion of a wider range of curriculum sharing, qualification mutual recognition and regional joint training.

4.3 Analysis on evolution results of localization of employment and entrepreneurship and homogenization of public services

The localization of employment and entrepreneurship and the homogenization of public services are important dimensions to measure the effectiveness of the joint construction and sharing of skilled talents in the Bay Area. The former reflects the regional absorption, retention and entrepreneurial undertaking ability of skilled talents, and the latter reflects the balanced degree and convenience level of cross-regional service supply. Figure 6 shows the time series change of localization level of employment and entrepreneurship.

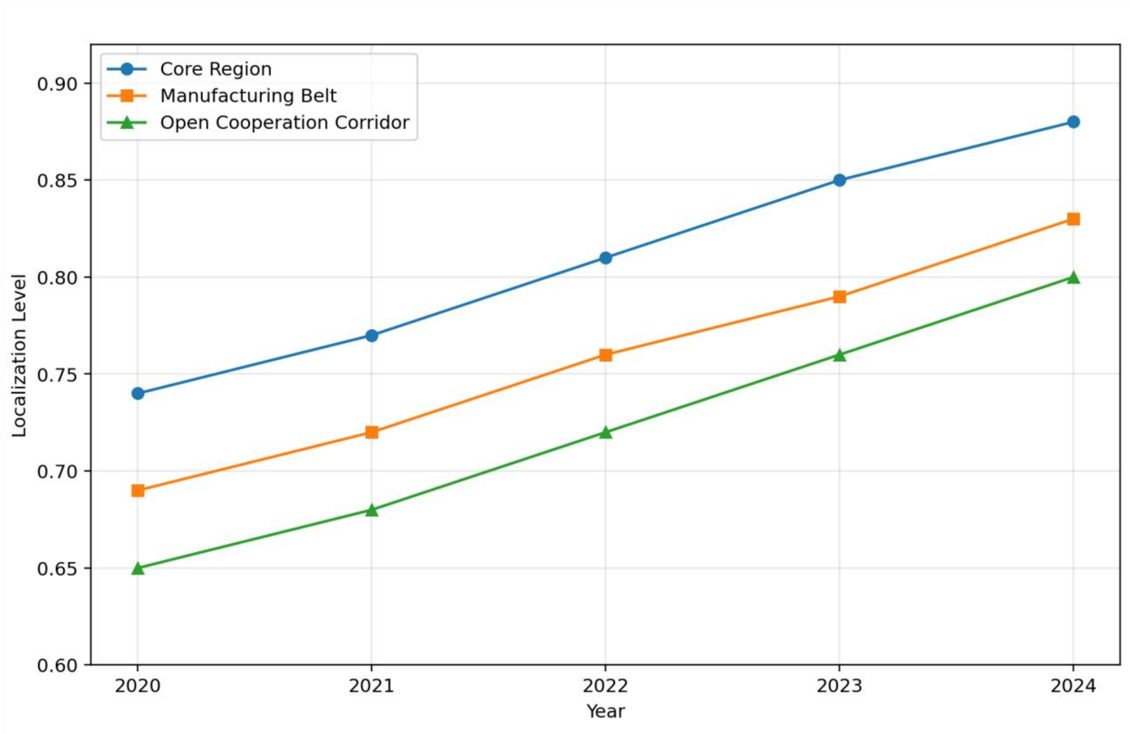

Figure 6: Time-Series Change in Employment and Entrepreneurship Localization

As can be seen from Figure 6, the localization level of various regions in the Bay Area shows a continuous upward trend from 2020 to 2024, and the core region increases from 0.74 to 0.88, with an increase of 18.9%. The manufacturing synergy band increased from 0.69 to 0.83, an increase of 20.3%; The open cooperation corridor increased from 0.65 to 0.80, an increase of 23.1 percent. This result shows that with the coordinated release of jobs, the linkage of entrepreneurial support and the extension of talent services, the skilled talents in the Bay Area have shown a strong growth momentum in local employment and entrepreneurial undertaking.

The comparison of homogenization levels of public services is shown in Figure 7.

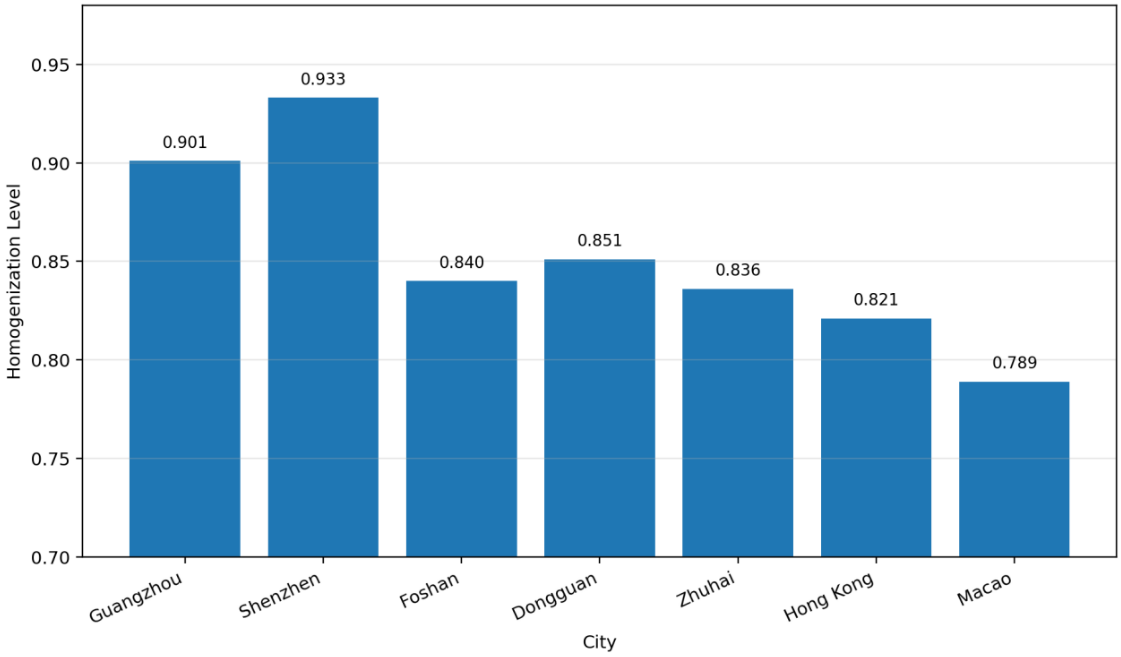

Figure 7: Comparison of Public Service Homogenization Level

As can be seen from Figure 7, the homogenization level of public service in Shenzhen is the highest, reaching 0.933, while that in Guangzhou is 0.901, and that in Foshan and Dongguan is 0.840 and 0.851 respectively. The values of Zhuhai, Hong Kong and Macao are 0.836, 0.821 and 0.789 respectively. Among them, the difference between Shenzhen and Macao is 0.144, indicating that there is still a gradient difference in the facilitation and equalization of public services within the Bay Area. In general, the speed of localization of employment and entrepreneurship is faster than the speed of equalization of public services. The joint construction and sharing of skills and talents in the Bay Area has achieved obvious results at the job undertaking end, but there is still room for further optimization of cross-regional service standard convergence and collaborative resource supply.

4.4 Analysis of collaborative matching results between Modern industrial College and key industrial chain

Modern industrial college is an important carrier connecting the training end of skilled talents and the demand end of key industrial chain, and its collaborative matching degree directly affects the structural efficiency of the co-construction and sharing of skilled talents in the Bay Area. Starting from the five key industrial chains of intelligent manufacturing, integrated circuits, biomedica, new energy and digital services, this paper measures the matching degree between the needs of modern industrial colleges and industrial chains. The matching degree matrix between modern industrial college and key industrial chain is shown in Figure 8.

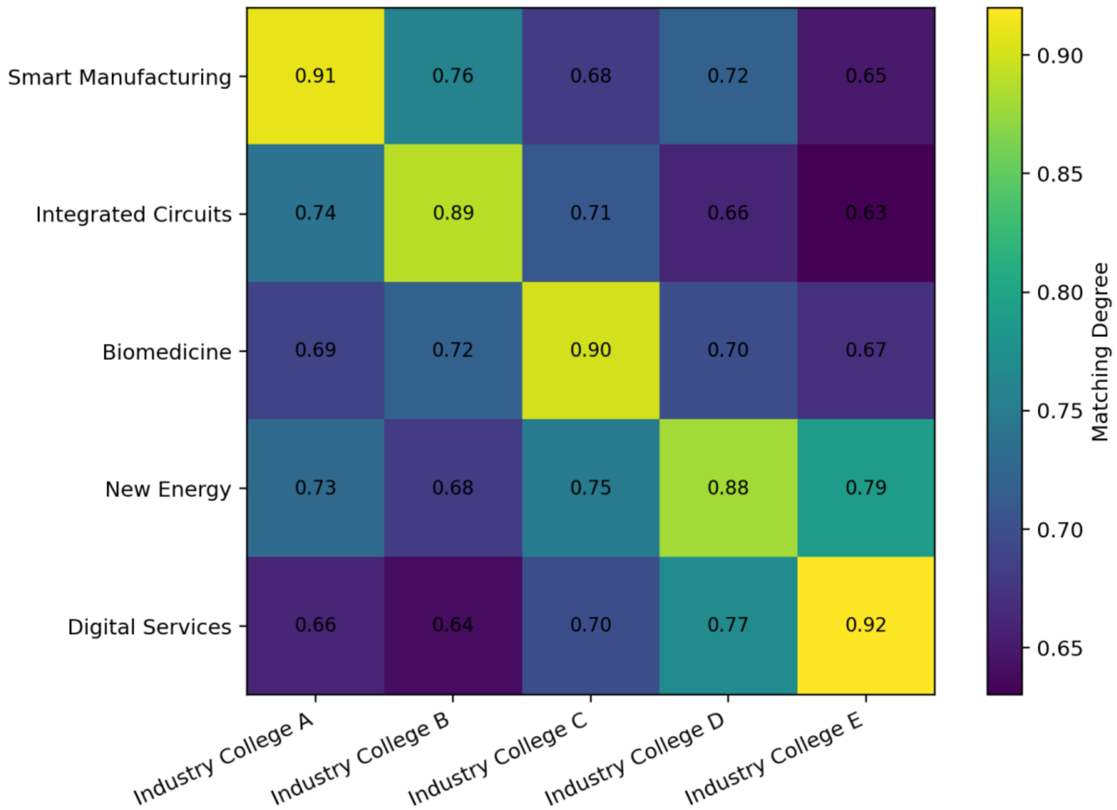

Figure 8: Matching Matrix of Modern Industry Colleges and Key Industry Chains

It can be seen from Figure 8 that intelligent manufacturing and industrial College A have the highest matching degree, reaching 0.91. College of Integrated Circuits and Industry B is 0.89; College of Biomedicine and Industry C is 0.90; D of College of New Energy and Industry is 0.88; The College of Digital Services and Industry had the highest E of 0.92. On the whole, the main diagonal matching value between each industrial chain and the corresponding industrial college is higher than 0.88, which is significantly higher than the lowest 0.63 in the non-corresponding relationship. This shows that the construction of modern industrial colleges in the Bay Area has initially formed a professional layout connected with key industrial chains, but there is still room for further improvement in the support ability of cross fields.

4.5 Simulation analysis of Chinese enterprises' "going global" service base and open deployment strategy of skilled talents

The construction of service bases for Chinese enterprises to "go global" is not only related to the efficiency of talent supply for overseas projects, but also directly affects the response ability of skilled talents in the Bay Area to be deployed across regions, industries and scenarios. In this paper, four kinds of strategies are set up to dynamically simulate the efficiency of open configuration, including benchmark scenario, training and capacity expansion scenario, service linkage scenario and comprehensive optimization scenario. Figure 9 shows the efficiency changes of open configuration under different policy scenarios.

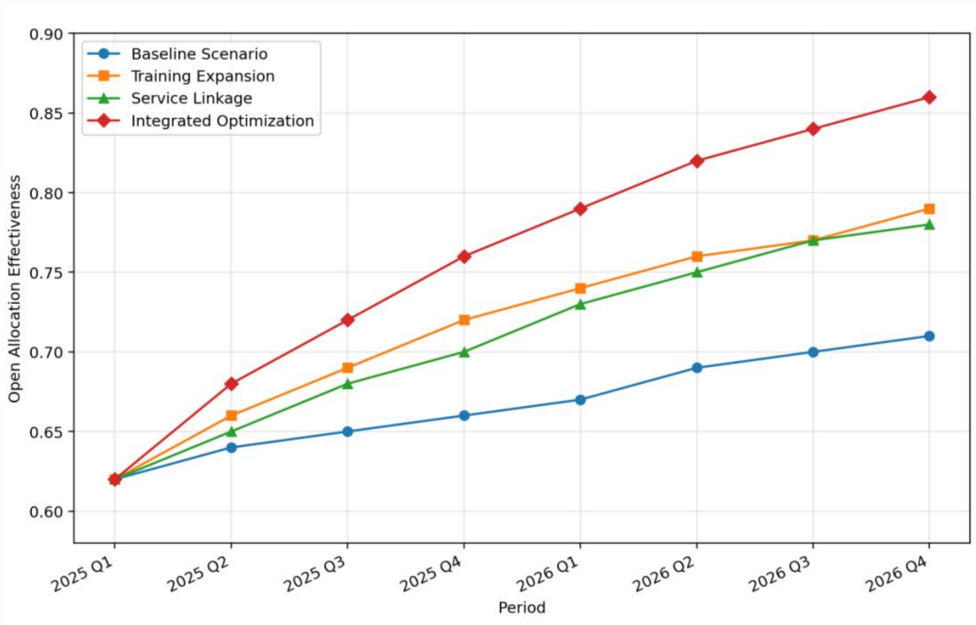

Figure 9: Changes in Open Allocation Effectiveness Under Different Strategy Scenarios

As can be seen from Figure 9, the efficiency of open configuration in the baseline scenario slowly increases from 0.62 to 0.71, with an overall increase of 14.5%. The training expansion scenario reached 0.79 at the end. The service interaction scenario reaches 0.78; The comprehensive optimization scenario has the fastest increase, from 0.62 to 0.86, and the cumulative increase is 38.7%. The results show that single capacity expansion or single service interaction can improve the allocative efficiency, but comprehensive optimization has more advantages in sustainability and improvement range.

In order to further compare the overall benefits of different strategies, this paper calculates the efficiency improvement in each scenario. The comparison of strategy simulation results is shown in Figure 10.

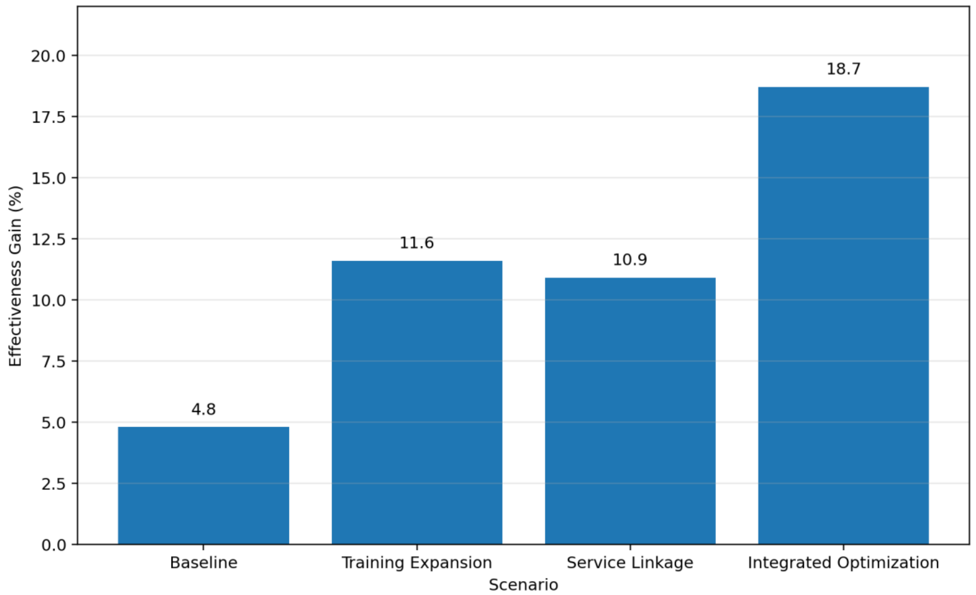

Figure 10: Comparison of Strategy Simulation Results

It can be seen from Figure 10 that the efficiency improvement rate of the benchmark scenario is only 4.8%, the training expansion scenario and the service linkage scenario reach 11.6% and 10.9% respectively, and the comprehensive optimization scenario has the highest improvement rate of 18.7%. In general, the comprehensive optimization scenario is 7.1 percentage points higher than the training expansion scenario, and 7.8 percentage points higher than the service linkage scenario. This shows that the collaborative allocation of service bases, training resources and post response mechanisms can more effectively support the open flow and international supply of skilled talents in the Bay Area.

4.6 Model ablation experiment

In order to verify the actual contribution of each key module to the performance of the model, this paper removes the knowledge graph relationship modeling module, spatio-temporal prediction module, strategy recommendation module and regional calibration module respectively based on the complete model, and conducts comparative tests under the same data set and parameter configuration. The results of ablation experiments are shown in Table 5.

Table 5: Comparison table of ablation experiment results

Model Configuration	RMSE	MAE	Shared Effectiveness Prediction Accuracy / %
Full Model	0.052	0.039	91.8
Without Knowledge Graph Module	0.067	0.051	87.6
Without Spatiotemporal Prediction Module	0.071	0.055	86.9
Without Strategy Recommendation Module	0.061	0.046	88.7
Without Regional Calibration Module	0.064	0.048	88.1

Table 5 shows that the full model performs best overall, with RMSE and MAE controlled at 0.052 and 0.039, respectively, and the shared efficiency prediction accuracy reaches 91.8%. After removing the spatio-temporal prediction module, the prediction accuracy dropped to 86.9%, which was 4.9 percentage points lower than that of the complete model, indicating that the time evolution information had the most obvious influence on the efficiency judgment. After removing the knowledge graph module, RMSE rises to 0.067, indicating that relationship modeling plays an important role in agent collaborative identification. On the whole, each module has a positive contribution to the performance improvement of the model, and the spatio-temporal prediction module and the knowledge graph module play a more prominent role.

5 Discussion

From the results, the joint construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area has formed a relatively clear gradient structure and network structure. The comprehensive recognition scores of Shenzhen and Guangzhou reached 0.912 and 0.901, respectively, indicating that the core cities had significant advantages in training resource agglomeration, job undertaking and platform linkage. The strength of the Guangzhou-Shenzhen relationship reached 0.91, and the Zhuhai-Macao relationship reached 0.88, indicating that cross-regional coordination has shifted from general cooperation to strong institutional cohesion and functional complementarity. This structural feature shows that the operational logic of the co-construction and sharing of skilled talents in the Bay Area is no longer stuck at the single point of resource investment level, but gradually presents the network evolution characteristics of "core leading, cross-border support and node diffusion".

Further, the localization level of employment and entrepreneurship continues to rise from 2020 to 2024, with the core area increasing from 0.74 to 0.88 and the open cooperation corridor increasing from 0.65 to 0.80, indicating that the collaborative release of jobs, the linkage of entrepreneurial support and service extension have a significant role in promoting talent retention and local absorption. In contrast, although the homogenization of public services has improved synchronously, there is still a gap of 0.144 between different cities, reflecting that service standards, platform interconnection and affairs are still important factors restricting regional balance. The matching values of the main diagonal of the modern industrial college and the key industrial chain are all higher than 0.88, indicating that the talent training mechanism oriented by the industrial chain has been initially established, but the support ability of cross fields still needs to be enhanced, otherwise the problem of insufficient local counterpart and overall linkage is prone to appear.

Policy simulation results further verify the necessity of collaborative governance. Under the comprehensive optimization scenario, the efficiency of open configuration was improved from 0.62 to 0.86, and the improvement rate reached 18.7%, which was significantly higher than that of single training expansion and single service linkage scenario. This shows that the support of skilled talents for Chinese enterprises to "go global" is inseparable from the synchronous adjustment of training system, service base and post allocation mechanism. In the ablation experiment, the prediction accuracy of the complete model reached 91.8%, which decreased by 4.9 percentage points after removing the spatio-temporal prediction module, which also showed that the co-construction and sharing of skilled talents in the Bay Area had significant time evolution characteristics, and static judgment was difficult to replace dynamic analysis.

Of course, there are some limitations in this paper. Although the scope of the data covers the main scenarios, the description of cross-border micro-mobility, intra-enterprise skill transfer and long-term tracking behavior is still insufficient. Some open cooperation data are greatly affected by the project cycle, and short-term fluctuations will perturb the local prediction results. Follow-up research can continue to expand cross-border continuous samples, and introduce more fine-grained job ability labels and service response data, so as to improve the model's ability to explain complex collaborative processes and the tracking accuracy of policy implementation effects.

6 Conclusion

Focusing on the problem of the co-construction and sharing of skilled talents in the Guangdong-Hong Kong-Macao Greater Bay Area, this paper constructs a technical analysis path consisting of data integration, standardization processing, knowledge graph relationship modeling, sharing network representation, spatio-temporal prediction and strategy recommendation, which achieves a unified description of regional collaboration status, subject relationship structure and efficiency evolution trend. The study found that the Bay Area has formed a collaborative pattern with Guangzhou and Shenzhen as the core and Shenzhen, Hong Kong and Zhuhai-Macao as the key fulpivoes. The localization level of the core region has increased from 0.74 to 0.88, the matching value of the main diagonal of the modern industrial college and the key industrial chain is higher than 0.88, and the efficiency improvement rate of the comprehensive optimization strategy has reached 18.7%. Ablation experiments show that the knowledge graph module and the spatio-temporal prediction module contribute most significantly to the performance, and the accuracy drops to 86.9% after removing the spatio-temporal prediction module. In general, the method proposed in this paper can better support the dynamic evaluation and strategy generation of the co-construction and sharing of skilled talents in the Bay Area. In the future, more fine-grained cross-border flow data and long-term tracking samples can be introduced to improve the generalization ability of the model and the accuracy of policy response.

References

[1] Zhu A Y F, Mok K H, Huang G H. Migrating to GBA Cities in Mainland China: Assessing a Model of Psychological Distance among Hong Kong Working Adults[J]. Analyses of Social Issues and Public Policy, 2021, 21(1): 579-594. DOI:10.1111/asap.12235.

[2] Ågren S. Exploring Vocational Education Students' Visions of a Successful Transition to Working Life from the Perspective of Societal Belonging[J]. Journal of Applied Youth Studies, 2021, 4(1): 67-81. DOI:10.1007/s43151-021-00037-5.

[3] Fuertes V, McQuaid R W, Robertson P J. Career-first: an Approach to Sustainable Labour Market Integration[J]. International Journal for Educational and Vocational Guidance, 2021, 21: 429-446. DOI:10.1007/s10775-020-09451-2.

[4] Fettach Y, Ghogho M, Benatallah B. Knowledge Graphs in Education and Employability: A Survey on Applications and Techniques[J]. IEEE Access, 2022, 10: 80174-80183. DOI:10.1109/ACCESS.2022.3194063.

[5] Wang Y, Shi Y. Evolvement of International Mobility of Talents: a Complex Network Perspective[J]. International Journal of Innovation Science, 2023, 15(2): 317-328. DOI:10.1108/IJIS-02-2021-0029.

[6] Guan J, Liu C, Liang G, Xing L. Framework to Measure the Mobility of Technical Talents: Evidence from China's Smart Logistics[J]. Sustainability, 2023, 15(3): 1-16. DOI:10.3390/su15032481.

[7] Shen C, Wang Y, Zuo J, Rameezdeen R. Leave or Stay? Antecedents of High-level Talent Migration in the Pearl River Delta Megalopolis of China: from a Perspective of Regional Differentials in Housing Prices[J]. Chinese Geographical Science, 2023, 33(6): 1068-1081. DOI:10.1007/s11769-023-1360-2.

[8] Ramos-Monge E, Fox P, Garcia-Piquer A. Addressing Soft Skill Gaps in the Digital Employment Market: the Case of Spanish Students in a Technology-Based University[J]. Education + Training, 2023, 65(6-7): 923-938. DOI:10.1108/ET-04-2023-0165.

[9] Michaelis C, Findeisen S. Long-term Effects of Different VET-to-Labor Market Transition Patterns on Subjective Well-being[J]. Zeitschrift für Erziehungswissenschaft, 2024, 27(2): 393-419. DOI:10.1007/s11618-023-01213-4.

[10] Gupta S L, Mittal A, Singh S, Dash D N. Demand-driven Approach of Vocational Education and Training (VET) and Experiential Learning: a Thematic Analysis through Systematic Literature Review (SLR)[J]. Asian Education and Development Studies, 2024, 13(1): 45-63. DOI:10.1108/AEDS-07-2023-0083.

[11] Kmiotek-Meier E, Rossié T, Canora K. All Good Things Come in Threes – Required Skill Sets in the Graduate Labour Market in Germany[J]. Education + Training, 2024, 66(10):

42-57. DOI:10.1108/ET-04-2023-0122.

[12] Zhong Z, Zong J. Universities as Cities of Flows: Decoding Cross-regional University Partnerships for Sustainable Development in China[J]. International Journal of Comparative Education and Development, 2024, 26(3): 208-225. DOI:10.1108/IJCED-08-2023-0075.

[13] Boškoski P, Redek T, Perne M, Boshkoska B M. Career Path Discovery through Bipartite Graphs[J]. Journal of Decision Systems, 2024, 33(sup1): 140-153. DOI:10.1080/12460125.2024.2354585.

[14] Suyitno, Nurtanto M, Jatmoko D, Widiyono Y, Purwoko R Y, Abdillah F, Setuju, Hermawan Y. The Effect of Work-Based Learning on Employability Skills: The Role of Self-Efficacy and Vocational Identity[J]. European Journal of Educational Research, 2025, 14(1): 309-321. DOI:10.12973/eu-jer.14.1.309.

[15] Fujiwara A. The Dynamics of International Talent Mobility and Knowledge Spillovers: Career Trajectories and Cross-Country Gaps in the Semiconductor Industry[J]. International Journal of Innovation Management, 2025, 29(09n10): 1-14. DOI:10.1142/S1363919625400171.

[16] Liu X, Yang Y, Derudder B, Witlox F. Emerging Synergies in Polycentric Cities? Exploring the Impact of Intercity Cooperation on Labour Market Integration in the Yangtze River Delta, 2014-2021[J]. Regional Studies, Regional Science, 2025, 12(1): 162-184. DOI:10.1080/21681376.2025.2472064.

[17] Nguyen N N, Tran Y, Nurgabdeshov A. International Entrepreneurial Mobility and Innovation: Revisiting the Phenomenon and Future Research Directions[J]. Journal of Global Mobility, 2025, 13(3): 445-467. DOI:10.1108/JGM-10-2024-0107.

[18] Xiao S, Sheng J, Zhang G. Rising Tides of Knowledge: Exploring China’s Higher Education Landscape and Human Capital Growth[J]. Journal of the Knowledge Economy, 2025, 16(1): 4392-4421. DOI:10.1007/s13132-024-02102-9.

[19] Hu X, Wan G, Zuo C. Education Development and Income Inequality: Evidence from China[J]. The Journal of Economic Inequality, 2025, 23(4): 1411-1432. DOI:10.1007/s10888-024-09656-3.

[20] Beber B, Lakemann T, Schnars R, Lay J. Employment Effects of Skills Trainings in Sub-Saharan Africa: A Systematic Review of Recent Randomized Controlled Trials[J]. De Economist, 2025, 173(1): 87-120. DOI:10.1007/s10645-024-09442-6.

[21] Gao Q, Mohamad M. A Conceptual Model of Learning Adaptability of Higher Vocational Students in China[J]. The Asia-Pacific Education Researcher, 2025, 34(3): 1063-1075. DOI:10.1007/s40299-024-00921-7.

[22] Zhang W, Balloo K, Hosein A, Medland E. “I Feel Happy Every Day, but I Also Feel Empty”: A Qualitative Investigation of Chinese Vocational College Students’ Well-being[J]. Social Indicators Research, 2025, 180(2): 997-1018. DOI:10.1007/s11205-025-03701-y.

[23] Naegele L, Schmitz W, Staniczek S, Heß M. Continuing Vocational Educational Training, Self-Directed Ageism, and Extending Working Lives: Evidence from the German Ageing Survey[J]. KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie, 2025, 77(4): 753-777. DOI:10.1007/s11577-025-01023-y.

[24] Wang G. Training the "Craftsmen of the Nation": Young People's Experiences of VET Reform in China[J]. Journal of Vocational Education & Training, 2025, 77(5): 1371-1391. DOI:10.1080/13636820.2025.2460004.