Research Article

Application of Multiattribute Decision-Making for Evaluating Regional Innovation Capacity

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The growing imbalance in regional innovation development has become an urgent issue in China's strategy to build an innovative country. To enrich the regional innovation capacity evaluation system, scientifically assess regional innovation capacity, and explore available pathways to improve regional innovation capacity, this paper introduces a multiattribute decision-making method for evaluating regional innovation capacity. First, a random forest model and the DEMATEL-based analytic network process (DANP) method are applied to calculate the weights of the evaluation attributes. Second, the multiobjective optimization by the ratio analysis method based on the maximum and minimum (MOORA-min-max method) is used to calculate the evaluation attribute gap ratios and regional innovation capacity of each region. Finally, the limitations of regional innovation development are identified based on the evaluation attribute gap ratios and the critical influence strength roadmap (CISR) to explore the regional innovation capacity improvement pathways. The results show that “output capacity of R&D personnel in universities and research institutes” is the most fundamental evaluation attribute in the regional innovation capacity evaluation, while “output efficiency of R&D funds in universities and research institutes” is the most influential evaluation attribute. Research in Sichuan and Inner Mongolia reveals that regions need to identify critical constraints in four aspects: knowledge creation, knowledge acquisition, enterprise innovation, and innovation environment, to improve regional innovation capacity.

1. Introduction

Persistent imbalance in the development of regional innovation capacity constitutes a substantial bottleneck constraining the effort to upgrade countries' integrated innovation capacity. China's regional innovation development is influenced by its history, economy, and geography and thus varies significantly [1–3]. To better promote the role of regional innovation in high-quality economic development, Chinese policymakers have placed innovation at the centre of overall national development. The 19th National Congress of the Communist Party of China proposed that “innovation is the first impetus for leading development” and issued a strategic plan to accelerate the construction of an innovation-oriented country.

Regional innovation capacity is an essential indicator of an innovation-oriented country, and many scholars have focused on regional innovation capacity in recent years

[4, 5]. Scholars have thoroughly studied the conceptual definition of regional innovation capacity, including its differences, indicators, influencing factors, and formation mechanisms [6–10]. For example, Shan constructed a system for evaluating regional innovation capacity based on four aspects: input capacity, innovation environment, management capacity, and innovation output [11]. Hamidi et al. examined the relationship between regional compactness and regional innovation capacity in the United States [12]. Tang et al. studied the spatial effect of absorptive capacity on regional innovation capacity from the perspective of knowledge spillover theory [13]. Many organizations have also published reports on the evaluation of innovation. The World Intellectual Property Organization and others cofounded the Global Innovation Index (GII), which ranks countries according to their innovation capacity and economic performance. Similarly, the National Research Group on S&T Development Strategy released the China Regional

Innovation Capability report, which provides an objective, dynamic, and comprehensive assessment of China's innovation capacity in each region.

With the advent of the Fourth Industrial Revolution, the ability to innovate has once again become a vital capacity for countries to compete for the right to global value distribution. For China, which displays significant differences in regional innovation development, improving regional innovation is an urgent issue. An accurate evaluation of regional innovation capacity is the basis for monitoring the current state of regional innovation development, identifying constraints on regional innovation development, and exploring pathways for improving regional innovation capacity. Accordingly, this paper selects evaluation indicators from four aspects, namely, knowledge creation, knowledge acquisition, enterprise innovation, and innovation environment and then applies the multiattribute decision-making method to evaluate the innovation capacity of all 31 provinces in China and to explore pathways for improving regional innovation capacity. The main contributions of this paper are as follows: (1) The random forest model and the decision-making trial and evaluation laboratory- (DEMATEL-) based analytic network process (DANP) method are introduced to innovation capacity evaluation research, thereby enriching the method for calculating objective weights; moreover, a multiattribute decision-making evaluation model of regional innovation capacity provides a new method to evaluate regional innovation objectively. (2) The multiobjective optimization by ratio analysis (MOORA) method and the critical influence strength roadmap (CISR) are introduced into the field of innovation research to provide a new approach to scientifically identify the factors limiting regional innovation capacity.

2. Literature Review

To date, scholars have not reached a consensus on how to evaluate regional innovation [14]. In the existing literature, innovation capacity evaluation research is divided into two aspects: evaluation indexes and evaluation methods. In terms of research on evaluation indexes, common indicators for evaluating regional innovation capacity include innovation resource inputs, innovation outputs, and innovation environments [15–17]. Other scholars have proposed patents as an essential indicator of regional innovation capacity [18–21]. For example, Hamidi et al. used the number of patents as one indicator of regional innovation capacity [12]. In addition, scholars have assessed the selection of indicators for evaluating regional innovation capacity in terms of system structure and green innovation. For example, Han et al. used the innovation participant framework [17] to classify innovation participants into eight categories, including government departments, research institutes, colleges and universities, enterprises, and technology intermediaries. They selected 63 innovation participant indexes to analyse the innovation capacity of 16 cities in Korea [22]. Chen et al. established regional innovation capabilities based on knowledge management from 6 aspects: knowledge base, knowledge creation, knowledge

dissemination, knowledge sharing, knowledge application, and innovation environment [23]. Wang et al. constructed a system of regional innovation evaluation indicators from green innovation inputs, green innovation outputs, and green innovation environments [24].

The research on evaluation methods for innovation capacity is divided into the calculation of evaluation index weights and the comprehensive evaluation of innovation capacity. The subjective weighting method and objective weighting method are the most common approaches for calculating the weights of evaluation indexes [25]. The former refers to weights determined subjectively through people's experience; for example, Shan developed a hierarchical analysis model of regional innovation capacity and used the analytic hierarchy process to calculate the weight of each evaluation indicator [11]. The latter refers to the analysis of the relationships between indicators based on objective data; for example, Yan et al. determined the indicator weights of regional technological innovation capacity by using the entropy method and empirically analysed the technological innovation capacity of 80 regions in Hubei Province, China [26]. Scholars have also proposed to comprehensively determine the weights of index combinations. For example, Xu et al. used the cloud model method and the entropy method to determine the initial weight of an index. Then, the cloud model was combined with the DEMATEL method to determine the final comprehensive weight of the indicator [27]. In terms of the comprehensive evaluation of innovation capacity, Sheng et al. used grey system theory and the Delphi method to establish a system of indicators for evaluating regional S&T innovation capacity. They then applied a new grey cluster model based on a mixed centre-point triangular whitenization weight function to evaluate the regional S&T innovation capacity of five cities in Jiangsu Province, China [28]. Yang et al. proposed a method based on uncertain linguistic variables for evaluating enterprise innovation capacity and analysed the innovation capacity of five firms [29]. Similarly, Zhen introduced the induced 2-tuple linguistic Choquet ordered harmonic average (I-2TCOHA) operator to aggregate the 2-tuple linguistic information corresponding to each alternative and rank the alternatives to evaluate the technological innovation capacity of a firm [30]. Li et al. proposed a multidimensional grey fuzzy decision-making method with feedback based on the weight vector and weight matrix and applied the method to evaluate regional financial innovation capacity [31]. Wang et al. used the fuzzy analytic hierarchy process to evaluate regional green innovation capacity [24].

In summary, the subjective evaluation method (represented by the analytic hierarchy process) determines evaluation indicator weights based on subjective ideas, while ignoring the information provided by data, resulting in the lack of an objective scientific basis for the resulting weights. In contrast, the objective evaluation method can effectively avoid subjective problems but suffers from certain deficiencies; for example, the entropy method ignores the lack of a horizontal comparison between indicators. The random forest model can calculate the influence strength among indicators, thereby avoiding the problem of subjectivity, and

thus can make comparisons between evaluation indicators. Existing scholars have performed a considerable amount of work on methods to evaluate innovation capacity and have proposed a series of policy recommendations; however, these suggestions are generally universal. Due to the differences among individual entities, the pathways to improving innovation capacity also vary. The MOORA method and critical influence strength roadmap (CISR) are introduced to evaluate innovation capacity; the former identifies the maximum gap ratio among the evaluation indicators, while the latter is a diagram showing the influence pathways among the evaluation indicators. The combination of these two can effectively identify the factors that restrict the development of individual innovation capacity and enables improvements in innovation capacity with individual differences.

3. Establishing the Indicator System and Building the Model

This section briefly introduces the construction of the indicators and models for evaluating regional innovation capacity. First, the main participants of the regional innovation system are universities, research institutes, companies, government agencies, and intermediaries [7, 17, 32], which are responsible for different roles: universities and research institutions with excellent researchers and sufficient innovation resources assume the role of knowledge creation; enterprises, as core participants in regional innovation systems, take on a greater role in transferring innovation knowledge; and government and intermediaries are responsible for providing a suitable environment for regional innovation. Second, the evaluation model uses the “drop-column importance” concept proposed by Terence et al. to measure the influence strength between evaluation indicators [33, 34]. The calculated influence strength is used as the raw data for the DANP approach, replacing the expert scoring approach. The DANP method is used to obtain a diagram of the influence strength network and the weight of each evaluation indicator. The MOORA method is then combined with maximum or minimum values to develop the MOORA-max-min method, which can calculate the gap ratio between the current level of an evaluation indicator and its maximum or minimum value. The regional innovation capacity is then calculated according to the weights of the evaluation indicators and the gap ratios. The model construction process is shown in Figure 1.

3.1. Establishing the Indicator System. The concept of the regional innovation system was first proposed by the British scholar Cooke in 1992. A regional innovation system is a regional organizational system formed by the division of labour, interconnected enterprises, universities, research institutions, intermediary services, and local governments within a specific geographical area [35]. Evaluation

indicators should consider the generation and application of knowledge and the underlying environment of regional innovation [36–39]. After analysing the characteristics and linkages of China’s regional innovation system, this paper constructs an evaluation indicator system from four aspects: knowledge creation, knowledge acquisition, enterprise innovation, and innovation environment. (1) Knowledge creation: knowledge creation is a source of regional innovation and refers to the process involving universities and research institutes, research funding, and inputs from researchers, including the inputs and outputs of innovation, measured mainly as research inputs, patents, and thesis outputs. (2) Knowledge acquisition: knowledge acquisition refers to the flow and utilization of knowledge within a region, measured mainly by thesis cooperation, corporate financial support, and the use of foreign investment. (3) Enterprise innovation: the translation of innovation results into products by firms is an important part of regional innovation. Corporate innovation is measured by corporate research inputs, patent outputs, and new product development. (4) Innovation environment: a good innovation environment can promote regional innovation. The innovation environment is measured mainly in terms of regional development, quality of intermediary services, and sustainability capacity. The resulting system of indicators for the evaluation of regional innovation capacity is shown in Table 1.

To guarantee the reproducibility of this study, the data in this paper come from publicly published statistical yearbooks and government reports, mainly including the China Statistical Yearbook, China Statistical Yearbook of Science and Technology, China Statistical Yearbook of High-Tech Industry, China Industry Economy Statistical Yearbook, China Torch Statistical Yearbook, statistical and analytical reports on Chinese science and technology papers, and related data released by the Ministry of Science and Technology, State Intellectual Property Office, State Administration for Industry and Commerce, and the Technology Innovation Fund for Science and Technology-based Small and Mid-Size Enterprises (SMEs).

3.2. Building the Multiattribute Decision-Making Evaluation Model of Regional Innovation Capacity

3.2.1. Using a Random Forest Model to Construct an Initial Influence Strength Matrix

Step 1: discretize the data for all evaluation attributes through a three-level interval discretization method comprising the top third (marked “H”), the middle third (marked “M”), and the bottom third (marked “L”) of the value range for each evaluation attribute [40].

Step 2: divide the n evaluation attributes ($x_1, x_2, \dots, x_n$) into n groups according to the individual evaluation attributes (called decision evaluation

FIGURE 1: Procedure of constructing the multiattribute decision-making evaluation model.

attributes x_1) and $n-1$ evaluation attributes (called conditional evaluation attributes $x_2, x_3, \dots, x_n$).

Step 3: use the random forest model to calculate the influence strength relationship among conditional evaluation attributes ($x_2, x_3, \dots, x_n$) and decision evaluation attributes (x_1); the calculated influence vector of conditional evaluation attributes $x_2, \dots, x_n$ on x_1 is $(a_{11}, a_{21}, \dots, a_{n1})$, where $a_{11} = 0$. Steps 2 and 3 are repeated n times for each decision variable x_i ($i = 1, 2, \dots, n$) to obtain n combinations of vectors. Furthermore, these n combinations of vectors are combined into an n -dimensional matrix $D = [d_{ij}]_{n \times n}$, where matrix D is called the direct influence strength matrix and d_{ij} represents the degree of influence of the i^{th} evaluation attribute on the j^{th} evaluation attribute when $i = j$, $d_{ij} = 0$. Steps 2 to 4 are repeated k times (k , one of the parameters of the random forest model, is the number of n estimators obtained through the

learning curve) to obtain k direct influence strength matrices D .

3.2.2. Applying the DANP Method to Draw the Influence Strength Network Diagram and Calculate the Evaluation Attribute Weights

Step 1: calculate the initial influence strength matrix. The k direct influence strength matrices D are measured by averaging them using the following equation to obtain the initial influence strength matrix A :

$$A = [a_{ij}]_{n \times n} = \left[\frac{\sum_{s=1}^k d_{ij}}{k} \right]_{n \times n}. \quad (1)$$

Step 2: normalize the initial influence strength matrix. The initial influence strength matrix A is converted by

TABLE 1: Regional innovation capacity evaluation indicator system

Primary indicators	Secondary indicators	Tertiary indicators	Description
Regional innovation capacity	Knowledge creation	Regional technology manpower investment (C1)	Average full-time personnel equivalent of research and experimental development per 10,000 population (person-years per 10,000 population)
		Regional government R&D investment (C2)	Government investment in R&D as a percentage of GDP (%)
		Output capacity of R&D personnel in universities and research institutes (C3)	Number of invention patent applications per 100 million yuan of internal expenditure on R&D (cases/billion yuan)
		Output efficiency of R&D personnel in universities and research institutes (C4)	Number of patents granted per 10,000 R&D personnel for inventions (pieces per 10,000)
		Output efficiency of R&D funds in universities and research institutes (C5)	Number of invention patents granted per 100 million yuan of internal expenditure on R&D activities (cases/billion)
		Publication of journal papers at home and abroad (C6)	Average number of papers published per 100,000 R&D personnel (per 100,000)
		Regional knowledge cooperation (C7)	Number of coauthored scientific and technical papers per 100,000 R&D staff (per 100,000)
		Cooperation between enterprises and universities and research institutes (C8)	The proportion of internal expenditure on research and development at universities and research institutes from corporate funds (%)
	Knowledge acquisition	Technology flow (C9)	Technical market transaction amount (by flow) (10,000 yuan)
		Enterprise acquisition of technical capabilities (C10)	Expenditure on the purchase/introduction of technology by industrial enterprises above scale (10,000 yuan)
		Regional ability to use foreign capital (C11)	Foreign share of registered capital of foreign-invested enterprises per capita at the end of the year (10,000 dollars)
		Enterprise R&D personnel input capability (C12)	Share of R&D personnel employed in industrial enterprises above scale (%)
	Enterprise innovation	Enterprise R&D funding investment capacity (C13)	Total internal expenditure on R&D activities of industrial enterprises above scale as a proportion of sales revenue (%)
		Enterprise R&D output capacity (C14)	Average number of invention patent applications per 10,000 R&D personnel in industrial enterprises above scale (pieces per 10,000)
		Enterprise core technology level (C15)	Average number of useful invention patents per 10,000 industrial enterprises above scale (pieces per 10,000 units)
		Enterprise new product development capability (C16)	Share of sales revenue from new products in sales revenue of industrial enterprises above scale (%)
		Regional market openness (C17)	Total exports and imports by destination and source of goods as a share of GDP (%)
		Regional talent training (C18)	Expenditure on education as a percentage of GDP (%)
		Quality of local workers (C19)	Proportion of the population aged six years and above with tertiary education (%)
		Financial institution support (C20)	Loans obtained from financial institutions out of the amount of internal expenditure on research and development of industrial enterprises above scale (RMB 10,000)
	Innovation environment	The proportion of high-tech enterprises (C21)	Number of high-technology enterprises as a proportion of the number of industrial enterprises above scale (%)
		Incubation capacity of technology business incubators (C22)	Number of technology business incubators graduating in a year (number of enterprises)
		Regional economic development level (C23)	Number of technology business incubators graduating in a year (number of enterprises) GDP level per capita (yuan/person)
		Regional sustainability (C24)	Integrated value of regional energy consumption and sewage emissions ¹

¹The integrated value is obtained after the dimensionless treatment of the energy consumption (equivalent value) of the regional GDP, the total power consumption, the total discharge of industrial sewage, and the discharge of major pollutants in the exhaust gas.

means of the following equations to obtain the normalized initial influence strength matrix Y :

$$Y = \Delta \times A, \quad (2)$$

$$\Delta = \min \left\{ \frac{1}{\max_i \sum_{j=1}^n a_{ij}}, \frac{1}{\max_j \sum_{i=1}^n a_{ij}} \right\}, \quad (3)$$

where Δ is the reciprocal of the maximum value of the sum of the rows or the columns of the initial influence strength matrix and is used to normalize the initial influence strength matrix.

Step 3: solve the total influence strength matrix. Based on the initial influence strength matrix D and the Markov chain matrix, the total influence strength matrix T is calculated using the following equation:

$$T = Y + Y^2 + \dots + Y^\infty = Y(E - Y)^{-1}, \quad (4)$$

where E is the n -dimensional identity matrix.

Step 4: draw the influence strength network diagram. The following equations are used to obtain g_i and r_i , and then the influence strength network diagram is plotted:

$$g_i = (g_i)_{n \times 1} = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1}, \quad (5)$$

$$r_i = (r_i)_{n \times 1} = (r_j)_{1 \times n}' = \left[\sum_{i=1}^n t_{ij} \right]_{1 \times n}', \quad (6)$$

where $'$ represents the matrix transposition and g_i represents the total influence strength of the i^{th} evaluation attribute on the other evaluation attributes, called the degree of influence of the i^{th} evaluation attribute. r_i represents the total influence strength of the other evaluation attributes on the i^{th} evaluation attribute and is called the degree of influence of the i^{th} evaluation attribute. The centrality degree $c_i = g_i + r_i$ reflects the importance of the i^{th} evaluation attribute in the system. The causality degree $h_i = g_i - r_i$, when $h_i > 0$, indicates that the i^{th} evaluation attribute is the causality attribute and influences the other evaluation attributes; if $h_i < 0$, then the i^{th} evaluation attribute is the result attribute and is influenced by the other evaluation attributes.

Step 5: build the unweighted supermatrix W and the weighted supermatrix W^w . The unweighted supermatrix W is calculated using the total influence strength

matrix T and equation (7). In addition, the unweighted supermatrix W is the weighted supermatrix W^w because all the evaluation attributes in this paper are of the same level:

$$W = W^w = (T^\Phi)' = \begin{bmatrix} \frac{t_{11}}{o_1} & \dots & \frac{t_{1j}}{o_1} & \dots & \frac{t_{1n}}{o_1} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{i1}}{o_i} & \dots & \frac{t_{ij}}{o_i} & \dots & \frac{t_{in}}{o_i} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{n1}}{o_n} & \dots & \frac{t_{nj}}{o_n} & \dots & \frac{t_{nn}}{o_n} \end{bmatrix}, \quad o_i = \sum_{j=1}^n t_{ij}. \quad (7)$$

Step 6: calculate the weights for each evaluation attribute. Equation (8) is iterated until the results converge to a stable limit supermatrix W^* to obtain the weights:

$$W^* = \lim_{\alpha \rightarrow \infty} (W^w)^\alpha. \quad (8)$$

3.2.3. Calculating Regional Innovation Capacity Using the MOORA-Min-Max Method

Step 1: establish a decision matrix. The decision matrix $U = [u_{xy}]_{m \times n}$, $x \in \{1, 2, \dots, m\}$, $y \in \{1, 2, \dots, n\}$, where m represents the number of regions, n represents the number of evaluation attributes, and u_{xy} represents the value of the y^{th} evaluation attribute in province x consisting of actual data from the 31 provinces in China.

Step 2: normalize the decision matrix. Given the quantitative variation among the indicators for the evaluation of regional innovation capacity, the decision matrix must be normalized. Equation (9) is rewritten as equation (10) based on the concept of range normalization:

$$u_{xy}^* = \frac{u_{xy}}{\sqrt{\sum_{x=1}^m u_{xy}^2}}, \quad (9)$$

$$u_{xy}^* = \frac{|u_y^{\max} - u_{xy}|}{(|u_y^{\max} - u_y^{\min}|)}. \quad (10)$$

Step 3: determine the gap ratio for each province. The gap ratio equation (11) is rewritten as equation (12) based on the normative decision matrix, and equation (13) is used to calculate the regional innovation capacity for each province:

$$Z_x^* = \sum_{y=1}^q w_y u_{xy}^* - \sum_{y=q+1}^n w_y u_{xy}^*, \quad (11)$$

$$Z_x^* = \sum_{y=1}^n w_y \cdot u_{xy}^*, \quad (12)$$

$$\text{RIC}_x = 1 - Z_x^*, \quad (13)$$

where w_y represents the weight of the y^{th} evaluation attribute, Z_x^* represents the gap ratio of regional innovation capacity in province x , and RIC_x represents the regional innovation capacity in province x .

4. Empirical Study

This paper applies the constructed multiattribute decision-making evaluation model of regional innovation capacity to assess the regional innovation capacity of the 31 provinces in China and to explore ways to improve regional innovation capacity.

4.1. Calculating the Direct Influence Strength between Evaluation Attributes Based on a Random Forest Model. After the three-level interval discretization of the original data, the evaluation attributes are divided into 24 groups according to the individual evaluation attributes (called decision attributes x_1) and 23 attributes (called conditional attributes $x_2, x_3, \dots, x_{24}$). Then, learning curves are used to train random forest models. For example, “regional technology manpower investment (C1)” is set as a decision attribute, C2 to C24 are set as the conditional attributes, and a learning curve is used for parameter tuning. These steps are repeated to determine that the value of k is 20. After k is determined, the direct influence strength between the evaluation attributes is calculated using a random forest model to obtain 20 direct influence strength matrices; then, the initial influence strength matrix A is obtained via equation (1), as shown in Table 2.

4.2. Drawing an Influence Strength Network Diagram and Calculating the Evaluation Attribute Weights Based on the DANP Method. The DANP method uses DEMATEL to calculate the total influence strength matrix of the evaluation attributes and then solves the evaluation attribute weights, and the method is used to draw an influence strength network diagram.

This paper calculates the accuracy of the random forest model and verifies the consistency of the 20 direct influence strength matrices before calculating the total influence strength matrix to ensure the reliability of the evaluation results. The former step tests the accuracy of the influence strength calculated by the random forest models, and the latter step tests the consensus among the 20 direct influence strength matrices. The random forest model typically uses the out-of-bag error (OOB error) rate to measure the model quality. As shown in Table 3, the average OOB error is between 0.01 and 0.26, with the evaluation attribute “cooperation between enterprises and universities and research institutes (C8)” having the worst quality and an average OOB error of 0.26 with an average accuracy of 74.20%. The evaluation attribute “regional technology manpower investment (C1)” has the highest quality with an average accuracy of 99%. A consistency test among the 20 direct influence strength matrices yields an average consistency gap ratio of 3.129% (less than 5%), as shown in Table 4, indicating that the 20 direct influence strength matrices have a high degree of consensus and that the results are reliable.

The initial influence strength matrix A is transformed by using equations (2) and (3) to obtain the normalized initial influence strength matrix Y . Then, matrix Y is calculated according to (4) to obtain the total influence strength matrix T (Table 5). Finally, the degree of influence (g_i), degree of being influenced (r_i), centrality degree (c_i), and causality degree (h_i) for each evaluation attribute are calculated using equations (5) and (6) (Table 6). Table 6 shows that evaluation attributes C1, C2, C3, C6, C10, C11, C17, C19, C20, C21, C22, and C23 are the cause attributes and C4, C5, C7, C8, C9, C12, C13, C14, C15, C16, C18, and C24 are the result attributes. The influence strength network diagram is then drawn according to the calculated centrality and causality of each evaluation attribute (Figure 2).

The influence strength network diagram visualizes the importance and grouping of each evaluation attribute (cause or result attribute), but it remains challenging to demonstrate the complex associations among each attribute. This paper introduces the concept of the net influence strength ζ to reflect the relation between each pair of attributes. The net influence strength ζ is the relative magnitude of t_{ij} and t_{ji} in the total influence strength matrix T , $\zeta_{ij} = t_{ij} - t_{ji}$. When $\zeta_{ij} > 0$, the i^{th} evaluation attribute greatly influences the j^{th} evaluation attribute, and C_i influences C_j ; when $\zeta_{ij} < 0$, C_j influences C_i . For example, $t_{13} = 0.013$ and $t_{31} = 0.042$ in the total influence strength matrix T , $\zeta_{13} < 0$, C3 influences C1, and thus, $\zeta_{13} = 0$, $\zeta_{13} = 1$ in the net influence strength matrix ζ . Additionally, given that influence strength exists between two or more evaluation attributes, ζ_{ij} is null when $i = j$. Similar calculations are repeated to obtain the net influence strength matrix ζ (Table 7). For the i^{th} evaluation attribute, $\zeta_{ij} = 1$ is grouped to obtain a net influence grouping for each evaluation attribute (Table 8). The number of net influence groupings indicates the net influence strength level of the

TABLE 2: Initial influence strength matrix.

A	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
C1	—	8.468	0.403	16.129	16.532	10.484	23.79	14.92	13.307	12.097	9.678	17.339	12.5	12.903	14.92	16.936	21.371	10.484	4.032	16.936	12.903	7.662	10.484	13.71
C2	8.871	—	0.403	18.952	12.097	10.887	28.629	17.339	10.887	11.291	7.662	15.323	14.516	14.516	14.113	8.871	7.661	10.081	6.855	10.887	5.242	6.452	10.081	10.484
C3	7.258	8.065	—	14.516	12.903	22.581	28.629	10.484	16.533	10.081	5.645	13.307	16.129	18.549	15.323	19.758	8.871	15.323	6.049	10.887	10.484	10.484	12.903	14.92
C4	9.678	8.468	3.629	—	111.694	9.678	31.855	27.42	14.92	4.839	6.452	8.871	13.307	18.145	15.726	19.758	14.516	8.065	5.645	10.081	9.678	7.662	10.484	16.533
C5	10.484	10.081	14.113	80.242	—	8.871	12.097	18.549	19.758	10.484	4.033	27.42	14.113	20.162	21.774	29.032	22.178	9.275	3.226	10.081	11.694	8.871	10.484	12.097
C6	11.291	10.081	3.629	15.726	14.92	—	41.129	25.807	9.275	8.871	6.049	15.323	27.823	10.887	14.92	19.758	11.694	60.081	4.839	10.887	16.129	8.065	18.145	38.71
C7	11.29	10.081	4.839	18.549	12.097	14.516	—	20.968	9.275	9.274	3.629	15.726	18.145	39.113	17.742	8.065	11.694	33.468	4.032	8.065	13.307	8.065	10.484	12.5
C8	13.307	7.258	3.629	14.516	22.178	13.307	14.516	—	14.516	8.871	5.242	22.178	23.387	9.678	8.871	18.952	4.839	32.662	2.823	10.081	10.081	17.339	10.484	30.645
C9	10.081	8.065	2.823	15.323	18.549	9.274	6.452	22.178	—	8.468	7.662	12.097	22.178	7.662	13.307	23.79	13.71	11.694	5.242	13.307	8.871	22.984	7.258	8.871
C10	14.92	8.065	2.419	13.307	17.339	14.92	9.274	20.161	9.678	—	7.662	16.532	31.855	12.903	20.161	18.952	11.694	14.92	5.645	11.291	16.129	4.839	6.452	23.387
C11	11.291	12.097	2.016	11.694	18.952	8.871	7.258	23.387	6.855	11.694	—	18.549	33.065	18.146	8.871	14.516	5.645	14.517	4.839	12.097	7.258	8.468	9.678	31.855
C12	8.871	7.662	2.016	17.742	17.339	10.081	11.694	12.5	9.678	11.694	6.049	—	37.097	20.565	14.113	35.081	8.871	18.145	5.645	11.291	14.516	6.855	8.468	14.516
C13	10.081	7.662	0.807	12.5	13.307	16.936	10.484	44.355	15.323	13.71	6.049	16.936	—	19.758	16.129	26.21	6.452	9.678	9.678	18.549	16.129	8.468	12.904	14.92
C14	8.468	7.258	2.823	16.936	44.758	18.549	38.71	14.92	8.871	11.694	8.871	13.307	10.081	—	13.71	16.533	11.291	27.016	5.242	8.065	8.065	7.258	10.081	6.452
C15	7.662	6.452	2.823	18.145	14.516	10.484	8.468	25	25	8.468	6.049	17.742	19.758	11.694	—	16.936	10.484	9.678	6.452	10.484	7.258	13.307	8.065	14.516
C16	5.242	6.452	6.452	13.307	44.758	10.484	30.242	28.226	17.742	7.258	4.839	20.161	29.839	15.726	11.694	—	14.516	12.097	5.242	10.081	10.484	13.71	14.92	14.516
C17	14.92	4.033	3.629	12.097	18.952	10.081	19.355	29.839	17.339	16.936	8.468	14.113	19.758	19.355	22.581	10.887	—	11.694	4.033	10.081	10.081	8.468	7.258	10.887
C18	6.452	11.291	4.032	12.097	16.533	31.855	14.113	12.097	14.113	5.645	5.242	14.92	11.291	16.936	22.178	16.936	8.468	—	7.662	12.5	8.871	12.5	10.081	23.387
C19	6.452	4.032	5.242	11.694	8.468	12.097	17.339	17.339	16.936	5.242	10.484	31.855	11.291	25.403	13.71	16.532	12.097	7.258	—	21.371	6.049	9.678	12.903	15.323
C20	8.871	8.065	4.839	12.903	13.71	16.936	17.742	27.016	14.113	5.645	9.678	27.823	20.565	20.565	12.904	11.694	5.242	7.258	4.032	—	12.5	8.065	17.742	11.291
C21	6.855	11.291	2.42	23.387	26.21	14.92	21.774	12.097	14.516	5.242	8.871	23.791	19.355	22.581	16.129	12.097	9.274	8.871	4.436	18.952	—	18.549	9.274	24.194
C22	7.258	8.871	3.629	14.517	17.742	16.533	12.5	19.355	12.5	5.645	7.662	20.565	12.5	20.565	20.968	11.694	4.839	10.484	1.613	10.887	13.71	—	8.871	21.774
C23	6.452	8.468	4.033	12.097	14.516	20.565	11.291	19.355	12.5	7.258	8.468	15.726	18.952	15.323	26.613	13.71	6.452	5.645	6.452	14.516	13.71	12.097	—	16.936
C24	7.258	11.694	2.419	14.113	8.065	15.323	24.194	23.387	10.484	7.258	7.258	10.484	18.549	16.533	25.403	22.581	7.258	22.178	13.307	16.129	17.742	12.5	9.678	—

TABLE 3: Average OOB error for each decision evaluation attribute.

Evaluation attribute	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
Average OOB	0.01	0.02	0.04	0.12	0.21	0.23	0.16	0.26	0.06	0.04	0.04	0.22	0.21	0.2	0.07	0.14	0.04	0.11	0.07	0.08	0.07	0.11	0.1	0.25
Accuracy (%)	99	98	95.7	88.1	78.6	77	84.5	74.2	93.8	95.6	96.1	78	79.3	80.5	93.1	85.9	95.7	88.6	93.1	91.6	93.1	89.3	90.2	74.7

$\text{oob_ave}_{C_n} = \sum_{s=1}^k \text{oob}_{C_{n,k}}/k$, where $\text{oob}_{C_{n,k}}$ represents the out-of-bag error (OOB error) rate of the evaluation attribute C_n as the decision evaluation attribute in the k^{th} random forest model, where $k = 20$.

TABLE 4: Consistency test results for the 20 direct influence matrices.

Number of matrices	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	No. 9	No. 10	No. 11	No. 12	No. 13	No. 14	No. 15	No. 16	No. 17	No. 18	No. 19	No. 20	Average
p	0.07345	0.062409	0.043803	0.037418	0.038652	0.036685	0.031286	0.031428	0.032798	0.031113	0.031761	0.027984	0.027597	0.027436	0.027384	0.027191	0.028	0.027765	0.029973	0.031675	0.03529
p (%)	7.345	6.241	4.38	3.742	3.865	3.668	3.129	3.143	3.28	3.111	3.176	2.798	2.76	2.744	2.738	2.719	2.8	2.777	2.997	3.167	3.529

$p = 1/n(n-1) \sum_{i=1}^n \sum_{j=1}^n |(f_{ij}^k - f_{ij}^{k-1}) / f_{ij}^k| < 5\%$, where f_{ij}^k represents the elements of the average influence strength matrix derived from k direct influence strength matrices.

TABLE 5: Total influence strength matrix

T	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
C1	0.028	0.041	0.013	0.087	0.101	0.06	0.099	0.091	0.065	0.05	0.038	0.083	0.081	0.076	0.076	0.085	0.071	0.069	0.024	0.067	0.058	0.046	0.051	0.075
C2	0.041	0.022	0.011	0.085	0.086	0.056	0.102	0.088	0.056	0.045	0.032	0.073	0.078	0.073	0.069	0.064	0.042	0.064	0.028	0.051	0.04	0.04	0.047	0.064
C3	0.042	0.041	0.012	0.085	0.097	0.085	0.112	0.085	0.073	0.047	0.031	0.077	0.09	0.089	0.079	0.092	0.049	0.082	0.029	0.057	0.055	0.052	0.057	0.08
C4	0.056	0.05	0.026	0.096	0.3	0.071	0.131	0.134	0.084	0.045	0.037	0.088	0.099	0.104	0.095	0.111	0.073	0.08	0.032	0.065	0.063	0.056	0.062	0.095
C5	0.056	0.052	0.042	0.223	0.114	0.069	0.099	0.119	0.091	0.054	0.034	0.116	0.101	0.105	0.104	0.126	0.084	0.08	0.028	0.065	0.066	0.058	0.061	0.087
C6	0.058	0.053	0.022	0.103	0.118	0.058	0.149	0.131	0.071	0.052	0.037	0.096	0.127	0.091	0.094	0.108	0.063	0.179	0.032	0.068	0.076	0.058	0.076	0.14
C7	0.05	0.046	0.021	0.093	0.099	0.072	0.06	0.104	0.06	0.046	0.028	0.082	0.092	0.126	0.084	0.072	0.055	0.116	0.025	0.052	0.06	0.048	0.053	0.076
C8	0.054	0.041	0.019	0.088	0.115	0.07	0.086	0.067	0.07	0.045	0.031	0.095	0.104	0.073	0.07	0.094	0.043	0.113	0.024	0.057	0.056	0.066	0.054	0.111
C9	0.045	0.039	0.017	0.082	0.102	0.056	0.064	0.101	0.038	0.041	0.033	0.071	0.095	0.062	0.07	0.095	0.055	0.067	0.025	0.058	0.049	0.073	0.044	0.064
C10	0.057	0.042	0.017	0.084	0.105	0.071	0.075	0.105	0.061	0.028	0.035	0.085	0.12	0.078	0.088	0.093	0.055	0.08	0.029	0.059	0.066	0.043	0.046	0.096
C11	0.049	0.048	0.015	0.079	0.105	0.059	0.07	0.108	0.054	0.049	0.02	0.086	0.119	0.085	0.066	0.083	0.042	0.077	0.027	0.059	0.049	0.048	0.05	0.11
C12	0.045	0.041	0.016	0.092	0.109	0.062	0.081	0.091	0.061	0.05	0.032	0.054	0.129	0.092	0.077	0.122	0.05	0.084	0.028	0.059	0.063	0.046	0.05	0.079
C13	0.049	0.042	0.014	0.084	0.102	0.076	0.081	0.15	0.073	0.054	0.033	0.089	0.064	0.092	0.082	0.108	0.046	0.074	0.036	0.074	0.067	0.051	0.059	0.084
C14	0.046	0.041	0.019	0.099	0.16	0.079	0.131	0.095	0.061	0.051	0.037	0.081	0.08	0.057	0.079	0.089	0.057	0.105	0.027	0.053	0.052	0.047	0.053	0.067
C15	0.04	0.036	0.016	0.087	0.095	0.058	0.067	0.106	0.085	0.041	0.03	0.081	0.091	0.069	0.045	0.083	0.049	0.064	0.028	0.053	0.046	0.055	0.045	0.074
C16	0.043	0.042	0.027	0.097	0.164	0.068	0.119	0.126	0.081	0.045	0.032	0.098	0.122	0.091	0.079	0.064	0.065	0.081	0.029	0.06	0.06	0.063	0.065	0.085
C17	0.057	0.033	0.019	0.081	0.106	0.061	0.091	0.119	0.074	0.059	0.036	0.079	0.095	0.088	0.091	0.076	0.032	0.073	0.024	0.055	0.054	0.048	0.045	0.072
C18	0.04	0.047	0.019	0.08	0.1	0.101	0.084	0.086	0.067	0.037	0.03	0.079	0.079	0.083	0.09	0.086	0.048	0.053	0.031	0.059	0.051	0.055	0.051	0.095
C19	0.04	0.032	0.021	0.076	0.085	0.063	0.087	0.094	0.071	0.037	0.04	0.11	0.079	0.099	0.073	0.085	0.053	0.064	0.016	0.075	0.045	0.049	0.056	0.078
C20	0.044	0.04	0.021	0.08	0.096	0.073	0.088	0.113	0.066	0.038	0.038	0.103	0.097	0.09	0.072	0.077	0.041	0.065	0.024	0.035	0.058	0.047	0.065	0.072
C21	0.044	0.05	0.018	0.109	0.13	0.074	0.103	0.094	0.073	0.04	0.039	0.102	0.1	0.101	0.085	0.084	0.053	0.073	0.027	0.075	0.038	0.07	0.053	0.1
C22	0.04	0.041	0.018	0.082	0.101	0.07	0.077	0.096	0.062	0.036	0.033	0.087	0.079	0.087	0.085	0.074	0.039	0.068	0.019	0.054	0.058	0.03	0.047	0.089
C23	0.039	0.041	0.019	0.078	0.095	0.078	0.075	0.098	0.063	0.04	0.035	0.08	0.092	0.078	0.096	0.079	0.042	0.06	0.029	0.062	0.059	0.054	0.031	0.081
C24	0.043	0.049	0.017	0.085	0.09	0.074	0.105	0.111	0.064	0.042	0.035	0.075	0.096	0.087	0.099	0.099	0.047	0.095	0.043	0.069	0.069	0.058	0.053	0.054

TABLE 6: Regional innovation capacity evaluation attributes of centrality and causality.

Evaluation attribute	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
Degree of influence (g_i)	1.535	1.355	1.6	2.052	2.036	2.062	1.621	1.649	1.447	1.616	1.557	1.614	1.685	1.67	1.443	1.805	1.567	1.553	1.531	1.544	1.734	1.475	1.503	1.658
Degree of being influenced	1.106	1.009	0.461	2.236	2.776	1.665	2.236	2.515	1.625	1.07	0.807	2.07	2.309	2.075	1.949	2.15	1.255	1.967	0.665	1.443	1.361	1.263	1.272	2.026
Centrality degree (r_i)	2.641	2.364	2.062	4.287	4.811	3.726	3.858	4.164	3.072	2.687	2.364	3.683	3.994	3.746	3.393	3.955	2.823	3.52	2.196	2.987	3.095	2.738	2.775	3.684
Ranking	20	22	24	2	1	8	6	3	14	19	21	10	4	7	12	5	16	11	23	15	13	18	17	9
Causality degree (h_i)	0.43	0.346	1.139	-0.184	-0.74	0.397	-0.615	-0.866	-0.178	0.546	0.75	-0.456	-0.624	-0.405	-0.506	-0.345	0.312	-0.414	0.865	0.101	0.373	0.212	0.231	-0.368
Group	Cause	Cause	Cause	Result	Result	Cause	Result	Result	Result	Cause	Cause	Result	Result	Result	Result	Result	Cause	Result	Cause	Cause	Cause	Cause	Cause	Result

FIGURE 2: Influence strength network diagram.

TABLE 7: Net influence strength matrix

ζ	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
C1	—	0	0	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1
C2	1	—	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0	1	1
C3	1	1	—	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C4	0	0	0	—	1	0	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1
C5	0	0	0	0	—	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0
C6	0	0	0	1	1	—	1	1	1	0	0	1	1	1	1	1	1	1	0	0	1	0	0	1
C7	0	0	0	0	1	0	—	1	0	0	0	1	1	0	1	0	0	1	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	—	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
C9	0	0	0	0	1	0	1	1	—	0	0	1	1	1	0	1	0	0	0	0	0	1	0	1
C10	1	0	0	1	1	1	1	1	1	—	0	1	1	1	1	1	0	1	0	1	1	1	1	1
C11	1	1	0	1	1	1	1	1	1	1	—	1	1	1	1	1	1	1	0	1	1	1	1	1
C12	0	0	0	1	0	0	0	0	0	0	0	—	1	1	0	1	0	1	0	0	0	0	0	1
C13	0	0	0	0	1	0	0	1	0	0	0	0	—	1	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	1	0	1	1	0	0	0	0	0	—	1	0	0	1	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	1	1	0	0	1	1	0	—	1	0	0	0	0	0	0	0	0
C16	0	0	0	0	1	0	1	1	0	0	0	0	1	1	0	—	0	0	0	0	0	0	0	0
C17	0	0	0	1	1	0	1	1	1	1	0	1	1	1	1	1	—	1	0	1	1	1	1	1
C18	0	0	0	1	1	0	0	0	1	0	0	0	1	0	1	1	0	—	0	0	0	0	0	0
C19	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	—	1	1	1	1	1
C20	0	0	0	1	1	1	1	1	1	0	0	1	1	1	1	1	0	1	0	—	0	0	1	1
C21	0	1	0	1	1	0	1	1	1	0	0	1	1	1	1	1	0	1	0	1	—	1	0	1
C22	0	1	0	1	1	1	1	1	0	0	0	1	1	1	1	1	0	1	0	1	0	—	0	1
C23	0	0	0	1	1	1	1	1	1	0	0	1	1	1	1	1	0	1	0	0	1	1	—	1
C24	0	0	0	0	1	0	1	1	0	0	0	0	1	1	1	1	0	1	0	0	0	0	0	—

evaluation attributes. When the number of net influence groupings is equal, further analysis of the net influence strength among these evaluation attributes is needed. For example, for the evaluation attributes C1, C2, and C10, the

net influence grouping is 18; in Table 8, C2 influences C1, and C10 influences C1. The relations between the evaluation attributes are clarified through net influence groupings, and the CISR is finally drawn (Figure 3).

TABLE 8: Net influence groupings.

Evaluation attribute	Net influence groupings	Number
C1	C4, C5, C6, C7, C8, C9, C12, C13, C14, C15, C16, C17, C18, C20, C21, C22, C23, C24	18
C2	C1, C4, C5, C6, C7, C8, C9, C10, C12, C13, C14, C15, C16, C17, C18, C20, C23, C24	18
C3	C1, C2, C4, C5, C6, C7, C8, C9, C10, C11, C12, C13, C14, C15, C16, C17, C18, C19, C20, C21, C22, C23, C24	23
C4	C5, C7, C8, C9, C13, C14, C15, C16, C24	9
C5	C8, C12, C15	3
C6	C4, C5, C7, C8, C9, C12, C13, C14, C15, C16, C17, C18, C21, C24	14
C7	C5, C8, C12, C13, C15, C18	6
C8	C12, C18	2
C9	C5, C7, C8, C12, C13, C14, C16, C22, C24	9
C10	C1, C4, C5, C6, C7, C8, C9, C12, C13, C14, C15, C16, C18, C20, C21, C22, C23, C24	18
C11	C1, C2, C4, C5, C6, C7, C8, C9, C10, C12, C13, C14, C15, C16, C17, C18, C20, C21, C22, C23, C24	21
C12	C4, C13, C14, C16, C18, C24	6
C13	C5, C8, C14	3
C14	C5, C7, C8, C15, C18	5
C15	C8, C9, C12, C13, C16	5
C16	C5, C7, C8, C13, C14	5
C17	C4, C5, C7, C8, C9, C10, C12, C13, C14, C15, C16, C18, C20, C21, C22, C23, C24	17
C18	C4, C5, C9, C13, C15, C16	6
C19	C1, C2, C4, C5, C6, C7, C8, C9, C10, C11, C12, C13, C14, C15, C16, C17, C18, C20, C21, C22, C23, C24	22
C20	C4, C5, C6, C7, C8, C9, C12, C13, C14, C15, C16, C18, C23, C24	14
C21	C2, C4, C5, C7, C8, C9, C12, C13, C14, C15, C16, C18, C20, C22, C24	15
C22	C2, C4, C5, C6, C7, C8, C12, C13, C14, C15, C16, C18, C20, C24	14
C23	C4, C5, C6, C7, C8, C9, C12, C13, C14, C15, C16, C18, C21, C22, C24	15
C24	C5, C7, C8, C13, C14, C15, C16, C18	8

The CISR illustrates that the “output capacity of R&D personnel in universities and research institutes (C3)” is the most prominent evaluation attribute of net influence strength and can be considered the most fundamental evaluation attribute, while the “cooperation between enterprises and universities and research institutes (C8)” is at the end of the CISR with the smallest net influence strength.

The unweighted supermatrix W and the weighted supermatrix W^w are obtained from equations (7) and (8), and multiplicative operations are performed on the weighted supermatrix W^w until the resultant convergent stable limit supermatrix W^* is obtained. Then, the weights for each evaluation attribute can be determined (Table 9).

4.3. Calculating Regional Innovation Capacity Based on the MOORA-Min-Max Method. This paper normalizes the data from the 31 provinces in China for 2017 using equations (10) and (12) and calculates the gap ratio, and the results are shown in Table 10. Finally, the regional innovation capacity and ranking of each province are calculated using equation (13), as shown in Table 11.

4.4. Exploring Regional Innovation Capacity Improvement Pathways Based on CISR. Table 11 illustrates the differences in regional innovation capacity among the 31

provinces in China. This paper explores regional innovation capacity improvement pathways to improve the imbalance in regional innovation capacity. Due to page limitations, the following presents an analysis of both the possible pathways for improving regional innovation capacity based on the CISR and the regional innovation capacity gap ratio using Sichuan and Inner Mongolia as examples.

As shown in Figure 4, Sichuan’s largest gap ratio is “enterprise new product development capability (C16),” which is influenced by “regional knowledge cooperation (C7),” “enterprise R&D personnel input capability (C12),” “enterprise R&D output capacity (C14),” “enterprise core technology level (C15),” and “regional talent training (C18)”: among these five evaluation attributes, C7 has the largest gap ratio. Therefore, regional knowledge cooperation could be enhanced to improve Sichuan’s regional innovation capacity. Inner Mongolia’s largest gap ratio is “output efficiency of R&D funds in universities and research institutes (C5),” which is influenced by “Enterprise R&D funding investment capacity (C13),” “enterprise R&D output capacity (C14),” “enterprise core technology level (C15),” and “enterprise new product development capability (C16)”: C16 has the largest gap ratio among these five attributes. Thus, Inner Mongolia should improve enterprises’ new product development capacity.

FIGURE 3: Critical influence strength roadmap (CISR).

4.5. Management Implications of the Multiattribute Decision-Making Evaluation Model. Regional innovation capacity provides a comprehensive description of regional innovation development. Improving regional innovation capacity does not involve only a single area of improvement but instead requires four main areas. (1) Knowledge creation: innovation resources are fundamental to knowledge creation. Regions need to increase investment in both human and material innovation

resources to increase innovation knowledge output. In addition, each region should improve the output efficiency of R&D personnel and R&D funding through measures such as optimizing the allocation of innovative resources. (2) Knowledge acquisition: cooperation is a meaningful way to fill resource gaps and achieve complementary strengths. Regional enterprises should strengthen financial support for universities and research institutes and actively introduce advanced technologies

TABLE 9: Regional innovation capacity evaluation attribute weights.

Evaluation attributes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
Weights	0.0282	0.0257	0.0121	0.0581	0.0717	0.0423	0.0559	0.064	0.0414	0.0273	0.0202	0.052	0.0582	0.0524	0.0493	0.0552	0.0321	0.0504	0.0171	0.0362	0.0348	0.0325	0.0322	0.0507

Gap ratio	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
Beijing	0	0	0.0097	0	0.0118	0	0.0285	0.0487	0	0.0213	0.0086	0.0083	0.011	0.0037	0	0.0241	0.0228	0.0439	0	0.0193	0	0.0207	0	0.0035
Tianjin	0.0136	0.0216	0.0103	0.0472	0.0551	0.0278	0.0421	0.0291	0.0326	0.0259	0.0108	0	0.0033	0.0391	0.0267	0.0134	0.0179	0.05	0.008	0.0329	0.0184	0.0293	0.0032	0.0029
Hebei	0.0255	0.0249	0.0115	0.0524	0.0598	0.0341	0.045	0.0516	0.0352	0.0249	0.02	0.0352	0.0297	0.0494	0.0473	0.0413	0.0271	0.0443	0.0161	0.0316	0.0308	0.0274	0.0268	0.0359
Shanxi	0.026	0.0255	0.0105	0.05	0.0462	0.0291	0.0435	0.0368	0.0364	0.0262	0.0201	0.0438	0.0382	0.0519	0.0438	0.0462	0.0295	0.0401	0.014	0.0336	0.032	0.0296	0.0279	0.0243
Inner Mongolia	0.026	0.0257	0.0121	0.0577	0.0717	0.0345	0.0429	0.0546	0.0384	0.0266	0.0199	0.0368	0.0325	0.042	0.0454	0.0474	0.0303	0.0418	0.0126	0.0334	0.0314	0.0287	0.0209	0.0247
Liaoning	0.0243	0.0224	0.0107	0.0371	0.0415	0.0162	0.039	0.0165	0.0355	0.0238	0.0167	0.0336	0.0163	0.0382	0.0381	0.0322	0.0218	0.0454	0.013	0.0336	0.0268	0.0273	0.0242	0.0243
Jilin	0.0251	0.0238	0.0099	0.0465	0.0257	0.0184	0.0415	0.0492	0.0375	0.0262	0.0201	0.0398	0.0488	0.0524	0.0493	0.0364	0.0295	0.0437	0.014	0.0354	0.0261	0.0289	0.0238	0.007
Heilongjiang	0.0261	0.0236	0.0094	0.0273	0	0.0022	0.0323	0	0.0394	0.0267	0.0201	0.0398	0.0258	0.0547	0.0446	0.0476	0.0301	0.0423	0.0147	0.0355	0.0302	0.0296	0.0279	0.0137
Shanghai	0.0113	0.014	0.0107	0.0218	0.0433	0.0154	0.0434	0.0486	0.0261	0.0041	0	0.0197	0.0061	0.02	0.026	0.011	0	0.0466	0.0058	0.0315	0.0188	0.0281	0.0008	0.0089
Jiangsu	0.0128	0.0247	0.0093	0.0357	0.0402	0.034	0.0515	0.0323	0.0215	0.0191	0.0141	0.0205	0.0138	0.0315	0.037	0.0255	0.016	0.0504	0.013	0.0203	0.0206	0	0.007	0.0434
Zhejiang	0.0126	0.0251	0.0094	0.0378	0.0289	0.0407	0.0554	0.0089	0.0315	0.023	0.0168	0.0137	0	0.0446	0.0461	0	0.016	0.0466	0.0137	0.0205	0.0274	0.0172	0.0118	0.0284
Anhui	0.0238	0.0236	0.0064	0.036	0.0307	0.0361	0.0528	0.0484	0.0359	0.0258	0.0199	0.0227	0.0228	0	0.0393	0.0229	0.0283	0.0425	0.0163	0.0317	0.0261	0.0276	0.0274	0.0168
Fujian	0.0207	0.025	0.0109	0.0433	0.0462	0.0394	0.0552	0.0361	0.0379	0.0215	0.017	0.0371	0.024	0.0394	0.0453	0.0439	0.0219	0.0484	0.0139	0.0271	0.0298	0.0275	0.0148	0.0142
Jiangxi	0.0259	0.0254	0.011	0.0547	0.0656	0.0347	0.0493	0.0347	0.0375	0.025	0.0194	0.0439	0.037	0.0408	0.0473	0.0407	0.0284	0.0396	0.0168	0.0326	0.0225	0.0283	0.0274	0.0119
Henan	0.0219	0.0252	0.0114	0.0455	0.0598	0.0388	0.0521	0.0371	0.0269	0.0199	0.0189	0.0284	0.0187	0.0333	0.045									

Gap ratio	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
Beijing	0	0	0.0097	0	0.0118	0	0.0285	0.0487	0	0.0213	0.0086	0.0083	0.011	0.0037	0	0.0241	0.0228	0.0439	0	0.0193	0	0.0207	0	0.0035
Tianjin	0.0136	0.0216	0.0103	0.0472	0.0551	0.0278	0.0421	0.0291	0.0326	0.0259	0.0108	0	0.0033	0.0391	0.0267	0.0134	0.0179	0.05	0.008	0.0329	0.0184	0.0293	0.0032	0.0029
Hebei	0.0255	0.0249	0.0115	0.0524	0.0598	0.0341	0.045	0.0516	0.0352	0.0352	0.0249	0.02	0.0352	0.0297	0.0494	0.0473	0.0413	0.0271	0.0401	0.0316	0.0308	0.0274	0.0268	0.0359
Shanxi	0.026	0.0255	0.0105	0.05	0.0462	0.0291	0.0435	0.0368	0.0364	0.0262	0.0201	0.0438	0.0382	0.0519	0.0438	0.0462	0.0295	0.0443	0.014	0.0336	0.032	0.0296	0.0279	0.0243
Inner Mongolia	0.026	0.0257	0.0121	0.0577	0.0717	0.0345	0.0429	0.0546	0.0384	0.0266	0.0199	0.0368	0.0325	0.042	0.0454	0.0474	0.0303	0.0418	0.0126	0.0334	0.0314	0.0287	0.0209	0.0247
Liaoning	0.0243	0.0224	0.0107	0.0371	0.0415	0.0162	0.039	0.0165	0.0355	0.0238	0.0167	0.0336	0.0163	0.0382	0.0381	0.0322	0.0218	0.0454	0.013	0.0336	0.0268	0.0273	0.0242	0.0243
Jilin	0.0251	0.0238	0.0099	0.0465	0.0257	0.0184	0.0415	0.0492	0.0375	0.0262	0.0201	0.0398	0.0488	0.0524	0.0493	0.0364	0.0295	0.0437	0.014	0.0354	0.0261	0.0289	0.0238	0.007
Heilongjiang	0.0261	0.0236	0.0094	0.0273	0	0.0022	0.0323	0	0.0394	0.0267	0.0201	0.0398	0.0258	0.0547	0.0446	0.0476	0.0301	0.0423	0.0147	0.0355	0.0302	0.0296	0.0279	0.0137
Shanghai	0.0113	0.014	0.0107	0.0218	0.0433	0.0154	0.0434	0.0486	0.0261	0.0041	0	0.0197	0.0061	0.02	0.026	0.011	0	0.0466	0.0058	0.0315	0.0188	0.0281	0.0008	0.0089
Jiangsu	0.0128	0.0247	0.0093	0.0357	0.0402	0.034	0.0515	0.0323	0.0215	0.0191	0.0141	0.0205	0.0138	0.0315	0.037	0.0255	0.016	0.0504	0.013	0.0203	0.0206	0	0.007	0.0434
Zhejiang	0.0126	0.0251	0.0094	0.0378	0.0289	0.0407	0.0554	0.0089	0.0315	0.023	0.0168	0.0137	0	0.0446	0.0461	0	0.016	0.0466	0.0137	0.0205	0.0274	0.0172	0.0118	0.0284
Anhui	0.0238	0.0236	0.0064	0.036	0.0307	0.0361	0.0528	0.0484	0.0359	0.0258	0.0199	0.0227	0.0228	0	0.0393	0.0229	0.0283	0.0425	0.0163	0.0317	0.0261	0.0276	0.0274	0.0168
Fujian	0.0207	0.025	0.0109	0.0433	0.0462	0.0394	0.0552	0.0361	0.0379	0.0215	0.017	0.0371	0.024	0.0394	0.0453	0.0439	0.0219	0.0484	0.0139	0.0271	0.0298	0.0275	0.0148	0.0142
Jiangxi	0.0259	0.0254	0.011	0.0547	0.0656	0.0347	0.0493	0.0347	0.0375	0.025	0.0194	0.0439	0.037	0.0408	0.0473	0.0407	0.0284	0.0396	0.0168	0.0326	0.0225	0.0283	0.0274	0.0119
Henan	0.0219	0.0252	0.0114	0.0455	0.0598	0.0388	0.0521	0.0371	0.0269	0.0199	0.0189	0.0284	0.0187	0.0333	0.045	0.0379	0.0228	0.0491	0.0147	0	0.0285	0.0158	0.018	0.047
Hubei	0.0251	0.0256	0.0101	0.0505	0.0528	0.0365	0.049	0.0408	0.0374	0.0259	0.02	0.0413	0.0399	0.0489	0.0478	0.0457	0.0284	0.044	0.0167	0.0279	0.0286	0.0216	0.0264	0.028
Hunan	0.0235	0.0232	0.0095	0.0409	0.0478	0.0212	0.0418	0.0305	0.0269	0.0235	0.0196	0.0264	0.0195	0.0371	0.0439	0.029	0.0296	0.0465	0.0134	0.0278	0.0266	0.0198	0.022	0.017
Guangdong	0.0246	0.0248	0.0105	0.0453	0.0572	0.0307	0.0487	0.0242	0.038	0.0255	0.0196	0.0326	0.0155	0.0363	0.0436	0.0198	0.0305	0.0447	0.0153	0.0324	0.027	0.0277	0.0255	0.0168
Guangxi	0.0172	0.0243	0.0104	0.0375	0.0373	0.0423	0.0559	0.0338	0.0097	0	0.0154	0.0265	0.0073	0.0099	0.0222	0.012	0.0049	0.0462	0.0144	0.0275	0.0162	0.0058	0.0154	0.0507
Guangzhou	0.0273	0.0248	0	0.0308	0.0045	0.003	0.0411	0.0545	0.0097	0.0265	0.0199	0.0501	0.048	0.0265	0.0465	0.0446	0.0262	0.0367	0.0171	0.0358	0.0288	0.0308	0.0291	0.013
Hainan	0.0271	0.0241	0.0095	0.0517	0.0462	0.0129	0.0162	0.064	0.0401	0.0272	0.0134	0.0341	0.0468	0.0353	0.028	0.0489	0.0257	0.0323	0.0148	0.0362	0.0138	0.0313	0.0258	0
Chungking	0.0231	0.0244	0.0105	0.0407	0.0444	0.0281	0.0469	0.0214	0.0367	0.0194	0.0188	0.0261	0.0089	0.04	0.043	0.0128	0.026	0.0426	0.0145	0.0309	0.0219	0.0296	0.021	0.0108
Sichuan	0.025	0.0207	0.0082	0.0403	0.0417	0.0267	0.0445	0.0408	0.03	0.0253	0.0199	0.0338	0.0346	0.0288	0.0407	0.0458	0.0285	0.0417	0.0158	0.0279	0.0252	0.0258	0.027	0.0234
Guizhou	0.0272	0.025	0.0066	0.0471	0.037	0.0314	0.0333	0.0454	0.0376	0.0259	0.0201	0.0365	0.0391	0.0313	0.0459	0.052	0.0311	0.029	0.0163	0.0332	0.0279	0.0313	0.0292	0.018
Yunnan	0.0268	0.0244	0.0106	0.0509	0.0509	0.032	0.0399	0.0518	0.038	0.0262	0.0201	0.0352	0.033	0.041	0.0445	0.0496	0.0296	0.0306	0.0167	0.0354	0.0296	0.0298	0.0304	0.0158
Tibet	0.0282	0.0252	0.0079	0.0581	0.0499	0.0324	0.0437	0.0618	0.0414	0.0273	0.02	0.052	0.0582	0.0474	0.0481	0.0546	0.0314	0	0.0168	0.0362	0.026	0.0325	0.0288	0.0018
Shaanxi	0.0231	0.0171	0.0078	0.0338	0.0386	0.0003	0.0264	0.0534	0.0303	0.0262	0.0194	0.0319	0.0293	0.0414	0.0406	0.0486	0.0284	0.0424	0.0138	0.0344	0.0246	0.0273	0.023	0.0134
Gansu	0.027	0.0226	0.0098	0.0488	0.0486	0.0064	0.0221	0.0429	0.0387	0.0272	0.0198	0.0384	0.0415	0.0394	0.045	0.0551	0.031	0.0229	0.0144	0.0353	0.0276	0.0296	0.0322	0.0105
Qinghai	0.0268	0.0246	0.0106	0.0534	0.0533	0.0248	0.0283	0.0555	0.0402	0.0273	0.0202	0.0471	0.0476	0.0487	0.0534	0.0321	0.0263	0.0154	0.0362	0.0252	0.0322	0.0272	0.0105	0.0168
Ningxia	0.0257	0.0238	0.0104	0.0456	0.0441	0.0329	0.0346	0.0625	0.0402	0.0271	0.0174	0.0362	0.0346	0.0266	0.0456	0.047	0.0297	0.0361	0.0137	0.0362	0.0333	0.0318	0.0251	0.0168
Sinkiang	0.0276	0.0255	0.0105	0.0486	0.0446	0.0069	0	0.0598	0.0397	0.0272	0.0202	0.0507	0.0472	0.0275	0.0479	0.0552	0.0263	0.0309	0.0126	0.0361	0.0348	0.0305	0.0269	0.0244

TABLE 11: Regional innovation capacity and ranking of China's 31 provinces.

Region	RIC	Ranking
Beijing	0.7141	1
Shanghai	0.538	2
Guangdong	0.4572	3
Tianjin	0.4388	4
Zhejiang	0.4239	5
Jiangsu	0.4059	6
Heilongjiang	0.3704	7
Chungking	0.3575	8
Liaoning	0.3416	9
Anhui	0.3363	10
Hubei	0.333	11
Shaanxi	0.3243	12
Hainan	0.2947	13
Hunan	0.2883	14
Shandong	0.2835	15
Sichuan	0.2779	16
Guangxi	0.2672	17
Gansu	0.2633	18
Fujian	0.2595	19
Guizhou	0.2427	20
Jilin	0.2409	21
Sinkiang	0.2381	22
Ningxia	0.2232	23
Yunnan	0.2092	24
Jiangxi	0.1996	25
Qinghai	0.1984	26
Shanxi	0.1947	27
Henan	0.181	28
Hebei	0.1721	29
Tibet	0.1704	30
Inner Mongolia	0.1619	31

both domestically and abroad. Regional R&D personnel should develop cooperation between science, technology, and innovation research to improve the output of scientific and technological papers and other results. Local governments should develop regionally appropriate policies to encourage foreign funding for regional innovation development. (3) Enterprise innovation: as essential participants in innovation transformation, enterprises must increase the output of their innovation results by increasing resource investment and conducting research on core technology. Additionally, enterprises should improve their new product development capabilities to achieve economic benefits. (4) Innovation environment: a good innovation environment is an important prerequisite for regional innovation development. Regions need to improve their talent training systems by increasing spending on education. Innovation intermediaries should fully play their role in supporting regional innovation by providing financial and facility resources for regional innovation. Finally, regional innovation should consider energy consumption, environmental pollution, and other issues to achieve sustainable innovation.

FIGURE 4: Regional innovation capacity improvement route.

5. Conclusion

This paper builds a multiattribute decision-making evaluation model of regional innovation capacity. The model uses a random forest model to determine the influence strength between evaluation attributes and obtains the objective weights of the evaluation attributes using the DANP method. Finally, the MOORA-min-max method is employed to calculate the

regional innovation capacity in each of China's 31 provinces and to explore regional innovation capacity improvement pathways. The empirical results suggest the following: (1) "Output capacity of R&D personnel in universities and research institutes (C3)" is the most fundamental evaluation attribute; this may be due to China's growing emphasis on industry-university-research as innovation-driven development strategies are proposed. Colleges and research institutes are essential subjects of industry-university-research. Therefore, C3 is the most fundamental evaluation attribute. (2) "Output efficiency of R&D funds in universities and research institutes (C5)" is the evaluation attribute with the largest weight. Given the emphasis on resource efficiency in regional innovation, C5 carries the greatest weight in regional innovation capacity evaluations. (3) Regional innovation capacity is an integrated reflection of innovation development, and enhancing regional innovation capacity involves identifying and addressing critical constraints.

Despite our efforts, two limitations provide ideas for future research. First, the evaluation indicator system constructed by different methods and innovation evaluation indicators (e.g., innovation policy) that are more difficult to monitor can affect the evaluation results, and future research needs to explore a more efficient evaluation indicator system. Second, the multiattribute decision-making evaluation model for regional innovation capacity proposed in this paper is a data-driven approach, and the parameters of the evaluation model ignore the subjective preferences of decision-makers, which should be considered in the future.

Data Availability

The readers can access the data from publicly published statistical yearbooks and government reports via the following links: <http://www.istic.ac.cn/tabid/640/default.aspx>, <http://www.most.gov.cn/>, <http://www.cnipa.gov.cn/tjxx/index.htm>, <http://www.saic.gov.cn/>, <http://www.stats.gov.cn/tjsj/ndsj/>, <http://tongji.cnki.net/kns55/navi/HomePage.aspx?id=N2019030267&name=YBVCX&floor=1>, <http://data.cnki.net/area/Yearbook/Single/N2018050242?z=D18>, <http://tongji.cnki.net/kns55/navi/HomePage.aspx?id=N2012110073&name=YZGJN>, <http://data.cnki.net/trade/Yearbook/Single/N201901Z0258?z=018>, <https://bbs.pinggu.org/thread-7955189-1-1.html>, <https://www.istic.ac.cn/tabid/640/default.aspx>, <http://www.most.gov.cn/>, <http://www.cnipa.gov.cn/tjxx/index.htm>, <http://www.saic.gov.cn/>, and <http://www.innofund.gov.cn/>.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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