

Construction of a Model for Evaluating the Effects of Regional Ethnic Autonomy Laws and Regulations Based on Differentiated Big Data Analysis

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Abstract: This paper constructs a model for evaluating the effectiveness of laws and regulations on ethnic regional autonomy based on differentiated big data analysis. It innovatively integrates the Fuzzy Best-Worst Method (FBWM), the CRITIC objective weighting method, and the principle of minimum discriminative information to form the FBWM-CRITIC combined weighting model. First, the current state of legislation for autonomous regulations and single-issue regulations is systematically reviewed, establishing four primary indicators: legal effectiveness (A1), political effectiveness (A2), economic effectiveness (A3), and social effectiveness (A4). These are further broken down into 18 secondary indicators and over 50 tertiary observational indicators. Through combined weighting, the core weights were determined: social effects (A4) accounted for 35.1%, political effects (A2) for 23.9%, highlighting the critical importance of human rights protection and public services; economic effects (A3) accounted for only 20.2%, with the lowest weight (0.034) among sub-indicators being technological development (B12). Model validation indicates that the FBWM consistency ratio (CR = 0.041–0.059) significantly outperforms AHP (CR = 0.075–0.132), and the combined weighting error rate is 23.7% lower than traditional additive/multiplicative synthesis methods. Applying this model to evaluate the implementation effectiveness of the five autonomous regions from 2015 to 2024 reveals that all dimensions are at the “qualified” level (60–70 points), with economic effectiveness being the best (66.79 points) and legal effectiveness being the weakest (63.06 points). The overall effectiveness improved by 47.2% over the decade (from an average of 0.443 in 2015 to 0.652 in 2024), Xinjiang (0.708) and Ningxia (0.692) maintained their lead, while Tibet showed significant fluctuations (from 0.385 in 2015 to 0.584 in 2024). Markov chain analysis revealed that the probability of low-level regions being locked in reached 88%, while high-level regions (Category IV) achieved 100% stability and exerted positive spillover effects on neighboring regions (increasing the transfer probability by 12%).

Keywords: ethnic regional autonomy; laws and regulations; combined empowerment; FBWM-CRITIC; minimum discriminative information principle

1. Introduction

As the rule of law enters a new era marked by shifts in the primary social contradictions, legal awareness among diverse social actors has significantly increased. The tangible benefits of the rule of law have drawn growing attention to the legal implementation effectiveness evaluation system, making it an indispensable component of the rule of law governance framework [1-2]. Current research on the legal implementation effectiveness evaluation system has received considerable attention in two areas: post-legislative evaluation at the local level and macro-level legal indicator monitoring [3]. The construction of the legal implementation effectiveness evaluation system requires systematic and holistic consideration in terms of theoretical foundations, content, and practical pathways, particularly in relation to the modernization of the national governance system and governance capabilities [4-5]. In the information age, leveraging big data analysis technology to construct a scientific evaluation system can



not only promptly identify issues with laws and regulations but also provide data support for optimization, holding significant implications for the construction of a rule-of-law society [6-8].

With the rapid development of big data technology, the use of big data analysis to enhance the construction of laws and regulations has become a research hotspot. For example, Custers [9] utilized big data analysis in legal issues and criminal law assessments, finding that this method has a positive impact on the evaluation and novelty of laws, and that the assessment system under big data analysis is more fair, reducing human errors and other issues. Kabir et al. [10] explored the impact of technologies such as the Internet of Things, big data, and artificial intelligence on the legal system, concluding that these technologies play a positive role in enhancing the efficiency and effectiveness of law enforcement and legal regulations. Simmons [11] applied big data predictive algorithms to the judicial system to improve its accuracy, efficiency, and fairness. The results indicated that when predictive algorithms are more transparent, their predictions are more likely to be accepted by the public. Subsequently, Busch [12] explored the design of disclosure authorization in consumer law and privacy law under big data and intelligent algorithms, demonstrating how to implement information technology adjustments to disclosure in consumer law and privacy law, and analyzing the impact of personalization on compliance supervision and enforcement. In the future, with the continuous advancement of technology and the ongoing improvement of systems, big data technology will play a greater role in legal regulation, providing strong support for the advancement of social civilization.

The article systematically reviews the current legal landscape, constructs a multi-dimensional indicator system, and develops an innovative combined empowerment model (FBWM-CRITIC-Minimum Discrimination Information Principle) to establish a comprehensive theoretical framework for evaluating the effectiveness of laws and regulations on ethnic regional autonomy. First, by systematically reviewing the current legislative status of existing autonomous regulations and separate regulations in ethnic autonomous regions, the article clarifies the specific connotations, developmental dynamics, and functional positioning of the evaluation objects in practice. Based on a profound understanding of the connotations of legal implementation effectiveness, a comprehensive and systematic three-tier evaluation indicator system is constructed. This system is structured around four key dimensions—legal effectiveness, political effectiveness, economic effectiveness, and social effectiveness—and is further broken down into 18 secondary indicators and over 50 specific, observable tertiary indicators. Given the characteristics of the indicator system being large-scale, complex interrelationships among indicators, and information possessing both subjective and objective attributes, the article innovatively proposes and elaborates on the FBWM-CRITIC grey system theory combination weighting model. Considering the ambiguity and uncertainty in experts' judgments of indicator importance, the fuzzy best-worst method (FBWM) is employed to calculate the subjective weights of indicators. This method involves experts identifying the best and worst indicators, conducting fuzzy pairwise comparisons, and using nonlinear optimization to obtain subjective weights that better reflect the consensus of the expert group. To overcome the limitations of purely subjective weighting and utilize objective data information, the CRITIC method is introduced to calculate the objective weights of the indicators. This method comprehensively considers the comparative strength of the indicators and the conflicts between them. Indicators with higher information content are assigned higher objective weights, ensuring the objectivity and data-driven nature of weight determination. To balance the influence of subjective and objective factors on the final evaluation results, the Minimum Discrimination Information Principle is applied to combine the subjective weights obtained from FBWM and the objective weights obtained from the CRITIC method.

2. Evaluation Index System and Empowerment Model Construction for the Effectiveness of Ethnic Regional Autonomy Laws and Regulations

2.1. Brief Overview of the Current Legal Situation Regarding Regional Ethnic Autonomy

From the autonomous regulations and separate regulations already enacted in ethnic autonomous regions, it can be seen that the two models of autonomous legislation have effectively fulfilled their respective functions in legislative practice. Regarding the basic situation of existing autonomous regulations, the regulatory texts are relatively uniform, consisting of several major sections: General Provisions, Autonomous Organs, Judicial Organs, Economic Development, Financial Management, Science, Education, Culture, and Health, Ethnic Relations, and Supplementary Provisions. In terms of content, the autonomous regulations provide a detailed interpretation of the autonomous rights of ethnic autonomous regions, serving both as a concretization of the Law on Regional Ethnic Autonomy and as an effective supplement to relevant provisions in ethnic legislation. Regarding the current situation of the formulation of single-issue regulations, the scope of social relations regulated by single-issue regulations

in ethnic autonomous regions has been gradually expanding. In recent years, new contents such as property management, administrative law enforcement, legal aid, urban heating, and the protection of the rights and interests of the elderly have been added to the regulations.

2.2. Evaluation Indicator System for the Effectiveness of the Implementation of the Legal System of Ethnic Regional Autonomy

This paper is based on the basic concepts of the evaluation index system for the implementation of the ethnic regional autonomy legal system. It uses four dimensions—legal effects, political effects, economic effects, and social effects—as first-level indicators, and sets corresponding second-level indicators and more specific third-level indicators to construct a three-level evaluation index system. The evaluation index system for the implementation of the ethnic regional autonomy legal system constructed in this paper is shown in Table 1.

Table 1. Evaluation System for the Effectiveness of laws on regional ethnic autonomy.

First-level indicator	Secondary indicators	Third-level indicators	Evaluation method
Legal effect (A1)	The system complies with legal provisions (B1)	B11: Whether the design of the legal system complies with legal rules	Qualitative
		B12: Whether the implementation of the system is conducive to the realization of legal purposes	Qualitative
	The system possesses institutional rationality (B2)	B21: Whether the rights and obligations of the system are reasonably allocated	Qualitative
		B22: Whether the implementation of the system conforms to the principle of proportionality	Qualitative
		B23: Whether the design of institutional links is reasonable and appropriate	Qualitative
	Institutional Design Science (B3)	B31: Whether the structure of the system design is logically sound and orderly	Qualitative
		B32: Whether the behavioral patterns of the system are efficient and convenient for the people	Qualitative
		B33: Whether the implementation of the system is operational	Qualitative
	Legal system: Due Process (B4)	B41: Whether the system procedure design is complete in every link	Qualitative
		B42: Whether program control reflects fairness and justice	Qualitative
		B43: Whether the implementation procedures of the system are open and transparent	Qualitative
		B44: Whether the public participation in the implementation of the system is	Qualitative

		relatively high	
Political effect (A2)	Consolidating the Party's Ruling Position (B5)	B51: The system implements the Party's policies and guidelines	Qualitative
		B52: The implementation of the system is conducive to national governance	Qualitative
		B53: The implementation results of the system are satisfactory to the masses	Qualitative
	Enhancing National Governance Capacity (B6)	B61: Democratization of national social governance decision-making	Qualitative
		B62: Standardization of national social governance behaviors	Qualitative
		B63: The scientific approach to national social governance	Qualitative
	Maintaining Social Order and Stability (B7)	B71: Maintain the stability of the existing social structure	Qualitative
		B72: Facilitates the normal implementation of social norms	Qualitative
	Economic effect (A3)	Impact on the overall economy (B8)	B81: Impact on the economic situation of the autonomous region
B82: Impact on the overall consumption level			Qualitative
B83: Impact on Economic and Industrial policies			Qualitative
Impact on the Market (B9)		B91: Impact on Rational Resource allocation	Qualitative
		B92: The impact on the regulation of supply and demand relations	Qualitative
		B93: Impact on active market competition	Qualitative
Impact on Business (B10)		B101: Impact on the operating costs of enterprises	Qualitative or quantitative
		B102: Impact on the administrative and economic burden of enterprises	Qualitative
		B103: Impact on the Future development of enterprises	Qualitative
		B104: The Impact on the Development of Small and Medium-sized Enterprises	Qualitative
The Impact on Consumer Households (B11)		B111: Impact on Personal Property Rights	Qualitative

		B112: Impact on Consumer Rights Protection	Qualitative
		B113: Impact on personal or family income and expenditure	Qualitative
	The Impact on Technological Development (B12)	B121: Impact on Technological Innovation	Qualitative or quantitative
		B122: Impact on Intellectual Property Protection	Qualitative or quantitative
		B123: The impact on the commercialization transformation of technology	Qualitative
	Social effect (A4)	The degree of advancement of institutional order (B13)	B131: Impact on the reduction of illegal acts
B132: The Impact on the Punishment of illegal and Criminal acts			Qualitative or quantitative
B133: Impact on the social security environment			Qualitative
B134: The Impact on legally encouraged behaviors			Qualitative or quantitative
B135: Impact on the Recognition of the Legal System			Qualitative or quantitative
Impact on Public Power Services (B14)		B141: The Impact on citizens' administrative burden	Qualitative
		B142: Impact on Administrative Disclosure	Qualitative
		B143: The Impact of citizens' Satisfaction with the government	Qualitative
The Impact on Human Rights Protection (B15)		B151: Impact on the Right to Equality	Qualitative
		B152: The impact on the exercise of political rights	Qualitative
		B153: Impact on citizens' Personal freedom	Qualitative
		B154: Impact on Personal Privacy Protection	Qualitative
		B155: The Impact on Social public order and good customs	Qualitative
Impact on Labor Employment (B16)		B161: Impact on the Protection of workers' rights and interests	Qualitative
		B162: Impact on the improvement of	Qualitative

		working conditions	
		B163: Impact on labor remuneration and welfare	Qualitative
	The Impact on Welfare Security (B17)	B171: The Impact on the Social security cause	Qualitative or quantitative
		B172: Impact on Social Security for Special Groups	Qualitative
	Impact on Cultural Undertakings (B18)	B181: The Impact on the Compulsory Education System	Qualitative
		B182: Impact on Young children and Higher education levels	Qualitative
		B183: The impact on the development of scientific research and artistic activities	Qualitative

The evaluation indicator system shown in Table 1 covers the broad impact of the four dimensions of law, politics, economy, and society, providing an observational framework for effectiveness evaluation. The legal effectiveness dimension focuses on the legitimacy, rationality, scientific nature, and procedural fairness of the system; the economic effectiveness dimension examines the impact on regional economy, markets, enterprises, consumption, science and technology, and other multi-level aspects; the social effectiveness dimension covers a wide range of areas including order maintenance, public power services, human rights protection, labor employment, welfare security, and cultural undertakings. The design of this indicator system aims to comprehensively and multi-dimensionally capture the comprehensive impacts of the implementation of laws and regulations on ethnic regional autonomy, providing clear target variables and observation points for subsequent differentiated big data analysis.

2.3. Construction of the FBWM-CRITIC Grey System Theory Model

To arrive at the final quantitative assessment results, it is crucial to scientifically determine the relative importance (weights) of each level of indicators in the comprehensive evaluation. Given the large number of indicators, the complex relationships between them, and the fact that the information involves both expert subjective judgment and objective data characteristics, a single weighting method is insufficient to meet the requirements. Therefore, this section proposes and constructs the FBWM-CRITIC grey system theory combination weighting model.

2.3.1. BWM-Based Indicator Weight Calculation Method

BWM is an MCDM technique first developed based on pairwise comparisons. Experts conduct pairwise comparisons of decision-making indicators based on their knowledge systems. Based on the ranking method process

The implementation of the BWM method includes five main steps, as follows:

(1) Determine the relative importance of the indicators;
(2) Each expert selects the best and worst indicators from the determined indicators;
(3) Compare the optimal indicator with other indicators in pairs. Each expert defines the importance level and selects the optimal indicator to compare with other indicators in pairs, obtaining the optimal opinion vector $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$, where a_{Bj} represents the weight of the optimal indicator relative to indicator j ;

(4) Compare the worst indicator with other indicators in pairs. Each expert selects the worst indicator based on its importance and compares it with other indicators in pairs to obtain the worst opinion vector $A_u = (a_{u1}, a_{u2}, \dots, a_{un})$, where a_{uj} represents the weight of the worst indicator relative to indicator j ;

(5) Optimal weights of decision indicators. The optimal weights of decision indicators can be represented by nonlinear optimization:

$$\left\{ \begin{array}{l} \min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{B_j} \right|, \left| \frac{w_j}{w_W} - a_{W_j} \right| \right\} \\ s.t. \\ \sum_j w_j = 1 \quad w_j \geq 0 \quad j = 1, 2, \dots, n \end{array} \right. \quad (1)$$

In the formula, w_s and w_j are the optimal indicator weights and the weight of indicator j , respectively.

From formula (1), we can see that the optimal weight of the indicator is the minimum of the maximum absolute difference between the weight ratio and the weight value, so it can be rewritten as

$$\left\{ \begin{array}{l} \min \xi \\ s.t. \\ \left| \frac{w_B}{w_j} - a_{B_j} \right| \leq \xi \\ \left| \frac{w_j}{w_W} - a_{W_j} \right| \leq \xi \\ \sum_j w_j = 1 \quad w_j \geq 0 \quad j = 1, 2, \dots, n \end{array} \right. \quad (2)$$

In the equation, ξ is a constant.

When the number of indicators exceeds three, equation (2) cannot obtain a single optimal solution, so it is linearized to obtain the following equation:

$$\left\{ \begin{array}{l} \min \xi^{1-} \\ s.t. \\ |w_B - a_{B_j} w_j| \leq \xi^{1-} \\ |w_j - a_{W_j} w_W| \leq \xi^{1-} \\ \sum_j w_j = 1 \quad w_j \geq 0, j = 1, 2, \dots, n \end{array} \right. \quad (3)$$

In the formula, ξ^{1-} is a constant.

Solving equation (3) yields the optimal weight of the decision indicator.

2.3.2. Indicator Weight Calculation Method Based on FBWM

In certain specific situations, experts and decision-makers are unable to overcome the ambiguity, subjectivity, and uncertainty of BWM when conducting pairwise comparisons. Therefore, the triangular fuzzy numbers are introduced into the original BWM method to form the FBWM method, thereby eliminating ambiguity and improving accuracy.

The main difference between BWM and FBWM lies in whether fuzzy numbers are used for pairwise comparisons. Each triangular fuzzy number (l, m, u) includes a lower bound (l), a middle bound (m), and an upper bound (u). Therefore, triangular fuzzy numbers can be used to encompass a broader range of expert opinions for pairwise comparisons.

The membership functions of triangular fuzzy numbers are as follows:

$$\mu_N(x) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leq m \\ 0 & x < l \text{ or } x > u \\ \frac{u-x}{u-m} & m \leq x \leq u \end{cases} \quad (4)$$

Fuzzy rule definition: If $A = (l_1, m_1, u_1)$ and $B = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, then the fuzzy operation is defined as follows:

$$A \oplus B = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (5)$$

$$A \ominus B = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \quad (6)$$

$$A \otimes B = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (7)$$

$$A^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right) \quad (8)$$

Fuzzify equation (2) according to the following equation:

$$\begin{cases} \min \tilde{\xi}^* \\ s.t. \\ \tilde{\xi}^* = (k^*, k^*, k^*) \\ \left| \frac{(I_B^*, m_B^*, u_B^*)}{(I_j^*, m_j^*, u_j^*)} - (I_B, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{(I_j^*, m_j^*, u_j^*)}{(I_0^*, m_0^*, u_0^*)} - (I_0, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^n R(\tilde{u}_j) = 1 \\ l_j^* \leq m_j^* \leq u_j^* \\ l_j^* \geq 0 \\ j = 1, 2, \dots, n \end{cases} \quad (9)$$

In the equation: $\tilde{\xi}^*$ is the triangular fuzzy number; k^* is a constant; $(I_B^v, m_B^v, u_B^v), (I_u^v, m_u^v, u_u^v), (I_j^v, m_j^v, u_j^v)$ are the fuzzy weights of the optimal, worst, and indicator j , respectively; $(I_{Bj}, m_{Bj}, u_{Bj}), (I_{wj}, m_{wj}, u_{wj})$ are the fuzzy weights of the optimal and worst indicators relative to indicator j ; \tilde{w}_j^* is the fuzzy weight of indicator j ; $R(\tilde{w}_j)$ is the precise weight of indicator j .

The following equation converts the fuzzy weight to the precise weight $R(\tilde{w}_j)$, which is expressed as the graded average integral of the fuzzy weight:

$$R(\tilde{w}_j) = \frac{l_j + 4m_j + u_j}{6} \quad j = 1, 2, \dots, n \quad (10)$$

Equations (9) and (10) can be used to calculate the optimal fuzzy weights $(\tilde{w}_1^*, \tilde{w}_2^*, \dots, \tilde{w}_n^*)$.

2.3.3. Calculating Objective Weights Using the CRITIC Method

(1) Overview of the CRITIC Method

The CRITIC method is a more objective weighting method than the entropy weighting method. Its basic idea is to comprehensively measure the objective weights of indicators by utilizing the conflict between indicators and the comparative strength of evaluation indicators. First, standard deviation can be used to represent the intensity of comparison. The larger the standard deviation of the data, the greater the volatility, and the higher the weight. Second, the correlation coefficient can be used to represent the conflict between indicators. The larger the correlation coefficient between indicators, the smaller the conflict, and thus the lower the weight. When calculating weights, the conflict indicators are multiplied by the intensity of comparison, and then normalized to obtain the final weights. Compared to the entropy weight method, the CRITIC method considers both the variability of indicators and the interrelationship between indicators. Therefore, a larger number does not necessarily indicate a more important indicator; instead, it is based on a scientific evaluation of the objective attributes of the data itself.

(2) CRITIC method calculation steps

Step 1: Construct the original indicator data matrix

Assuming there are n samples to be tested and p evaluation indicators, the original indicator data matrix can be constructed as follows:

$$X = \begin{pmatrix} X_{11} & \cdots & X_{1p} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{np} \end{pmatrix} \quad (11)$$

where X_{ij} represents the value of the p th evaluation indicator for the i th sample.

Step 2: Dimensionless processing

Since different indicators have different dimensions, which can affect the evaluation results, it is necessary to normalize or inverse the dimensions of each indicator. If the indicator is a positive indicator, it is processed using equation (12); if the indicator is an inverse indicator, it is processed using equation (13).

$$X'_{ij} = \frac{X_j - X_{\min}}{X_{\max} - X_{\min}} \quad (12)$$

$$X'_{ij} = \frac{X_{\max} - X_j}{X_{\max} - X_{\min}} \quad (13)$$

Step 3: Calculate the variability between indicators.

The standard deviation can be used to express the variability between indicators, and the standard deviation represents the difference in fluctuations between the values of each indicator. If the difference in the values of the indicators is greater, the corresponding standard deviation will be greater, and the importance of the indicator itself will be higher, so the indicator will be assigned a higher weight. The formula is as follows:

$$\begin{cases} \bar{X}_j = \frac{1}{n} \sum_{i=1}^n X_{ij} \\ S_j = \sqrt{\frac{\sum_{i=1}^n (X_{ij} - \bar{X}_j)^2}{n-1}} \end{cases} \quad (14)$$

S_j denotes the standard deviation of the j th indicator.

Step 4: Calculation of indicator conflict

The correlation between indicators can be expressed using the correlation coefficient. The stronger the correlation between an indicator and other indicators, the smaller the conflict between that indicator and other indicators, and the more similar information the indicators carry, leading to more repetitive evaluation content. This weakens the importance of the indicator to a certain extent, so the weight assigned to that indicator will be reduced. The conflict between indicators is calculated using the correlation coefficient, with the formula shown below:

$$R_j = \sum_{i=1}^p (1 - r_{ij}) \quad (15)$$

r_{ij} represents the correlation coefficient between evaluation indicators i and j .

Step 5: Calculate the information content of indicators

C_j is the information content of the j th indicator. The larger the value of C_j , the greater the importance of the j th evaluation indicator in the entire evaluation indicator system, and the more weight it will be assigned. The calculation formula is as follows:

$$C_j = S_j \sum_{i=1}^p (1 - r_{ij}) = S_j \times R_j \quad (16)$$

Step 6: Weight calculation

W_j is the objective weight of the j th indicator, calculated using the following formula:

$$W_j = \frac{C_j}{\sum_{j=1}^p C_j} \quad (17)$$

2.3.4 Calculation of Combination Weights

A single weighting method has certain limitations and cannot fully reflect all the characteristics of each decision-making data. Using a combination of objective and subjective weighting methods to weight each indicator is the best way to deal with this kind of problem. Academic circles often employ the following mathematical methods for combination weighting: combination weighting of multi-attribute decision-making objectives based on the principle of maximizing deviation; optimal combination weighting of subjective and objective comprehensive weights proposed based on the sum of squared deviations; combination weighting based on decision-makers' subjective and objective preferences and information entropy; and combination weighting of fuzzy preferences and fuzzy AHP to determine indicator weights.

Inspired by the above methods, and considering the characteristics of each indicator in the evaluation system for the implementation effects of the ethnic regional autonomy legal system, to balance the influence of subjective and objective factors on the evaluation results, the principle of minimum discriminative information is adopted for combined weighting after a systematic analysis of the characteristics and applicability of each combination method.

(1) Overview of the Principle of Minimum Discriminative Information

The basic idea of the minimum discriminant information principle is to select $q(x)$ from among those that satisfy the constraints $\int q(x) f_m(x) dx = C_m$ and $\int q(x) dx = 1$, such that the discriminant

information $I(q(x), p(x)) = \int q(x) \log \frac{q(x)}{p(x)} dx$ takes the smallest value as the estimate for $q(x)$.

This is because among the $q(x)$ that satisfy $\int q(x) f_m(x) dx = C_m$ and $\int q(x) dx = 1$, the $q(x)$ that

minimizes $I(q(x), p(x)) = \int q(x) \log \frac{q(x)}{p(x)} dx$ is minimal, meaning that the amount of information

required to change from $p(x)$ to $q(x)$ is minimal, or in other words, the distribution that minimizes the discriminative information is the distribution that is closest to $p(x)$ under the constraints. Introducing

the Lagrange multiplier $F = \int q(x) \log \frac{q(x)}{p(x)} - \beta q(x) - \sum_{m=1}^M \lambda_m q(x) f_m(x) dx$, take the variation of

the above function with respect to $q(x)$ and set it equal to zero. According to Euler's equation, this is equivalent to requiring that the partial derivative of the integrand with respect to $q(x)$ be zero. Let

$\log \frac{q(x)}{p(x)} + 1 - \beta - \sum_{m=1}^M \lambda_m f_m(x) = 0$, we obtain $q(x) = p(x) \exp[\lambda_0 + \sum \lambda_m f_m(x)]$, where $\lambda_0 = \beta - 1$. λ_0 and $\lambda_m (m=1, 2, \dots, M)$ can in principle be obtained from the $M+1$ constraints $\int q(x) f_m(x) dx = C_m$ and $\int q(x) dx = 1$.

The magnitude of the multiplier reflects the extent to which the constraint affects the distribution; a constraint corresponding to a zero multiplier indicates that $p(x)$ is the prior probability, and values close to $p(x)$ indicate minimal discriminative information.

(2) Calculation steps for the principle of minimal discriminative information

Let the subjective weight be $W1(j)$, the objective weight be $W2(j)$, and the combined weight be $W(j)$. Establish the objective function:

$$\begin{aligned} \min F &= \sum_j^m W(j) \left[\ln \frac{W(j)}{W_1(j)} \right] + \sum_j^m W(j) \left[\ln \frac{W(j)}{W_2(j)} \right] \\ \text{s.t. } &\sum_{j=1}^m W(j) = 1; W(j) > 0 \end{aligned} \quad (18)$$

According to the Lagrange multiplier method, the combination weights are obtained as follows:

$$W(j) = \frac{[W_1(j)W_2(j)]^{0.5}}{\sum_{j=1}^m [W_1(j)W_2(j)]^{0.5}} \quad (19)$$

3. Weight Determination and Comparison Based on FBWM-CRITIC Combination Weighting

This paper constructs a composite weighting model based on the FBWM-CRITIC-minimum discriminative information principle. To verify the scientific validity and applicability of this model in the evaluation of ethnic regional autonomy regulations, Chapter 3 will use this model to calculate indicator weights and conduct a dual verification of its superiority through a comparison of identification methods and optimization of combination methods.

3.1. Using FBWM to Determine the Weights of Each Indicator

The evaluation indicator system listed in Section 2.2 was adopted, resulting in a total of 4 main indicators and 18 sub-indicators, which were determined by 10 experts after review. Among the main indicators, A4 is the optimal indicator, and A3 is the least optimal indicator.

After converting the experts' linguistic evaluations into triangular fuzzy numbers, the comprehensive fuzzy weights for each main indicator and sub-indicator were calculated. The CRITIC method was used to convert the fuzzy weights into precise numerical values. The results of the fuzzy weights for each main indicator and sub-indicator are shown in Table 2.

Table 2. The fuzzy weight results of each main indicator and sub-indicator.

Main indicator	Fuzzy weight of the main indicator	R	Sub-indicator	Fuzzy weights of sub-indicators	Comprehensive fuzzy weight	R	Sorting
A1	(0.218, 0.245, 0.271)	0.208	B1	(0.152, 0.178, 0.204)	(0.033, 0.044, 0.055)	0.047	13
			B2	(0.138, 0.162, 0.189)	(0.030, 0.040, 0.051)	0.043	14
			B3	(0.201, 0.235, 0.256)	(0.044, 0.058, 0.069)	0.061	6
			B4	(0.186, 0.217, 0.241)	(0.041, 0.053, 0.065)	0.057	8
A2	(0.285, 0.312, 0.336)	0.239	B5	(0.241, 0.268, 0.295)	(0.069, 0.084, 0.099)	0.091	1
			B6	(0.208, 0.231, 0.254)	(0.059, 0.072, 0.085)	0.078	2
			B7	(0.187, 0.209, 0.233)	(0.053, 0.065, 0.078)	0.070	3
A3	(0.193, 0.221, 0.248)	0.202	B8	(0.158, 0.182, 0.207)	(0.030, 0.040, 0.051)	0.043	14
			B9	(0.176, 0.201, 0.226)	(0.034, 0.044, 0.056)	0.048	12
			B10	(0.142, 0.163, 0.189)	(0.027, 0.036, 0.047)	0.040	16
			B11	(0.132, 0.152, 0.173)	(0.025, 0.034, 0.043)	0.037	17
			B12	(0.124, 0.142, 0.165)	(0.024, 0.031, 0.041)	0.034	18
A4	(0.231, 0.257, 0.284)	0.351	B13	(0.206, 0.232, 0.258)	(0.048, 0.060, 0.073)	0.065	5
			B14	(0.188, 0.211, 0.237)	(0.043, 0.054, 0.067)	0.059	7
			B15	(0.225, 0.251, 0.276)	(0.052, 0.065, 0.078)	0.070	4
			B16	(0.173, 0.198, 0.223)	(0.040, 0.051, 0.063)	0.055	9
			B17	(0.162, 0.184, 0.209)	(0.037, 0.047, 0.059)	0.052	10
			B18	(0.154, 0.176, 0.201)	(0.036, 0.045, 0.057)	0.050	11

Table 2 shows the fuzzy weights and comprehensive weights of the main indicators and sub-indicators calculated using the FBWM method. The social impact (A4) is the optimal indicator, with a comprehensive weight of 0.351 (fuzzy weights: 0.231, 0.257, 0.284), significantly higher than other dimensions (A2: 0.239; A1: 0.208; A3: 0.202). This indicates that both the expert group and objective data consider the implementation effects of the social dimension (such as human rights protection, public services, and social welfare) to occupy a central position in the evaluation system. Political effects (A2) rank second (0.239), followed by legal effects (A1) and economic effects (A3) in third (0.208) and fourth (0.202) places, respectively.

Among the sub-indicators, B5 (consolidating the Party's ruling position) leads with an R value of 0.091, with the highest comprehensive fuzzy weights (0.069, 0.084, 0.099) among the 18 sub-indicators, reflecting the fundamental requirement of policy effectiveness assessment for political direction. B6 (enhancing national governance capabilities, R value 0.078) and B7 (maintaining social order and stability, R value 0.080) rank second and third, respectively, the three together form the core observation points for political effectiveness. B15 (Impact on Human Rights Protection) ranks first among the A4 sub-indicators with a weight of 0.070, highlighting the importance of social foundational rights such as

citizens' equality rights and political rights. B13 (Progress in Institutional Order) (0.065) and B14 (Impact on Public Power Services) (0.059) follow closely behind, reflecting high attention to social security and government service efficiency. Sub-indicators under the economic dimension have the lowest overall weights, with B12 (Impact of Technological Development, 0.034) and B11 (Impact on Consumer Rights, 0.037) ranking at the bottom (overall rankings 17-18), indicating that economic impacts have relatively lower priority in the assessment.

The weight distribution in Table 2 scientifically reflects the multidimensionality, political orientation, and practical complexity of the assessment of the effectiveness of ethnic regional autonomy laws and regulations. The high priority of social human rights indicators provides a key focus for differentiated big data analysis, while the weight structure of economic effects suggests the need to capture their implicit impacts through long-term dynamic data. This result validates the effectiveness of the FBWM-CRITIC combined model in balancing expert consensus and data objectivity.

3.2 Comparison and Analysis of Different Identification Methods and Weight Combination Methods

3.2.1 Comparison of Identification Methods

Based on the same experts and basic data, an AHP-WEWM-LDM model was established and compared with the FBWM-CRITIC model. The comparison of the weight calculation results of the two identification models is shown in Figure 1. As can be seen from Figure 1, although the weight values of the risk indicators of the two models are different, the weight rankings are roughly the same. This shows that the risk identification process based on the FBWM-CRITIC model has a certain degree of reliability and effectiveness.

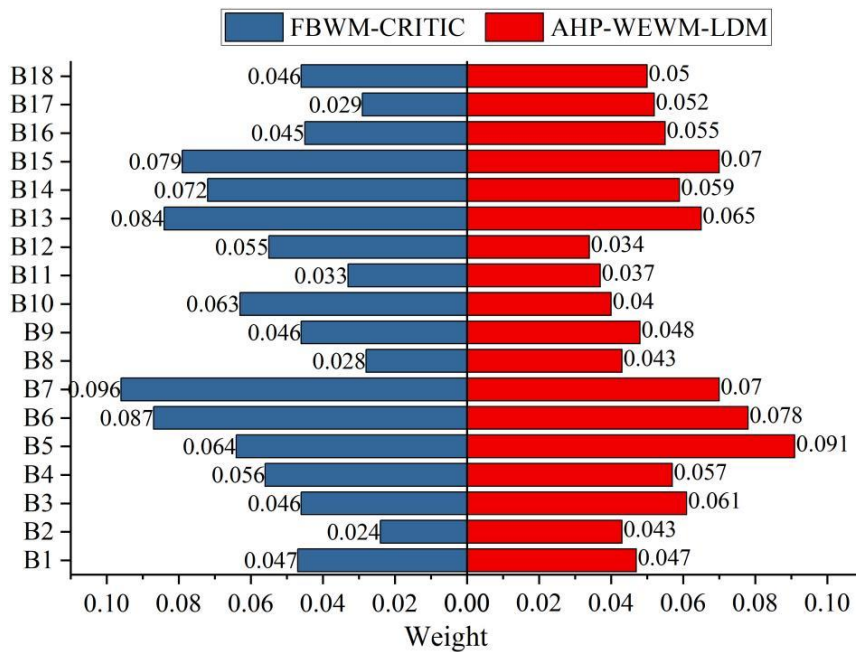


Figure 1. Comparison of the weight calculation results of the two recognition models.

To further validate the reliability and effectiveness of the FBWM-CRITIC model, a consistency comparison was conducted between the subjective methods of the FBWM-CRITIC model and the AHP-WEWM-LDM model, namely the fuzzy best-worst method and the analytic hierarchy process (AHP). Consistency testing was conducted using three metrics: consistency ratio (CR), inverse order number (MV), and total error (TD). The consistency comparison results between the fuzzy best-worst method and the AHP are presented in Table 3.

Table 3. Consistency comparison between FBWM and AHP.

	FBWM			AHP		
	CR	Mv	TD	CR	Mv	TD

A1-A5	0.056	0.045	0.071	0.081	0.067	1.745
B1-B4	0.045	0.038	0.079	0.075	0.079	0.949
B5-B7	0.041	0.052	0.081	0.106	0.088	1.904
B8-B12	0.052	0.054	0.065	0.132	0.081	2.033
B13-B18	0.059	0.034	0.094	0.088	0.074	1.536

As shown in Table 3, the CR, MV, and TD values of the evaluation matrices at each level in the Fuzzy Optimal-Suboptimal Method are all smaller than the corresponding values in the AHP, indicating a higher degree of consistency. This is because the fewer comparison criteria (only maximum and minimum risk) reduce the likelihood of logical errors, and secondly, triangular fuzzy numbers effectively quantify the fuzziness of evaluation variables. In the calculation of single-layer consistency ratio CR, FBWM (0.041–0.059) is lower than AHP (0.075–0.132), and AHP exceeds the threshold of 0.1 at the 50% level, requiring correction. Furthermore, for n indicators, the fuzzy optimal-worst method only requires $2n$ comparisons, which is far fewer than the n^2 comparisons required by the AHP method, and no correction is needed, resulting in shorter computation time and higher accuracy. In summary, incorporating the fuzzy optimal-worst method into the FBWM-CRITIC risk identification model not only effectively ensures the reliability and validity of the weight solution results but also improves the accuracy and efficiency of risk identification.

3.2.2. Comparison of Weighting Methods

To demonstrate the rationality and effectiveness of the weight combination of the FBWM-CRITIC model, traditional additive synthesis and multiplicative synthesis methods were used for subjective and objective integration, and the results were compared with those obtained by objective weighting methods. The results are shown in Table 4.

Table 4. Comparison of weight calculation results under three combination methods.

Indicator	Additive synthesis	Multiplication synthesis	CRITIC	MAX	MIN	SD
B1	0.057	0.055	0.047	0.057	0.044	0.005
B2	0.045	0.026	0.043	0.045	0.033	0.010
B3	0.058	0.062	0.061	0.062	0.056	0.002
B4	0.054	0.045	0.057	0.064	0.046	0.006
B5	0.093	0.083	0.091	0.093	0.072	0.005
B6	0.065	0.056	0.078	0.078	0.052	0.011
B7	0.074	0.101	0.070	0.093	0.087	0.015
B8	0.052	0.065	0.043	0.065	0.042	0.011
B9	0.057	0.075	0.048	0.075	0.049	0.013
B10	0.046	0.027	0.040	0.046	0.022	0.009
B11	0.025	0.011	0.037	0.045	0.013	0.012
B12	0.019	0.029	0.034	0.037	0.016	0.007
B13	0.085	0.097	0.065	0.094	0.066	0.016
B14	0.041	0.073	0.059	0.075	0.046	0.016
B15	0.053	0.045	0.070	0.071	0.043	0.012
B16	0.076	0.065	0.055	0.074	0.048	0.010
B17	0.032	0.049	0.052	0.066	0.025	0.010
B18	0.068	0.036	0.050	0.072	0.043	0.015

In Table 4, the region between the minimum and maximum risk weights represents the reasonable range for combination weights. As shown in Table 4, the combination weight rankings obtained using the additive synthesis method and the CRITIC method are generally consistent, but there are significant differences in some weight values, reflecting the substantial discrepancies in how experts and data assess the importance of such indicators. For example, the weight of B14 (public power services) reaches 0.073 in the multiplicative synthesis method, while it is only 0.059 in the CRITIC method, with a difference of 23.7%. The former has a higher evaluation value but lower volatility, while the latter has a lower evaluation value and lower volatility.

The entropy weight method determines weights based on the volatility of each indicator's data, leading to discrepancies between the objective weight rankings and actual conditions. The additive synthesis method fails to mitigate this impact, resulting in distorted outcomes for some results. The multiplicative synthesis method yields results with high distinguishability, but some values exceed reasonable ranges, resulting in low reliability of the composite values. The maximum difference method distinguishes between favorable and unfavorable information in the subjective and objective weight information, ensuring that the FBWM-CRITIC model calculations have a high degree of practical conformity, the danger levels of various risk indicators have obvious distinctions, and the combined weight values are constrained within a reasonable range, thereby balancing the advantages of subjective and objective weights and achieving a reasonable and effective combination method.

4. Assessment of the Effectiveness of Ethnic Regional Autonomy Laws and Regulations and Analysis of Regional Differences

Through the FBWM-CRITIC combination weighting in Chapter 3, it has been confirmed that social effects (A4) account for the core weight (35.1%) in the evaluation system, and the model has passed consistency testing ($CR < 0.06$) and combination method optimization verification. Based on this weighting result, Chapter 4 will further conduct an actual quantitative evaluation of policy effects and analyze regional differences among the five autonomous regions.

Taking China's ethnic autonomous regions as the research object, this paper evaluates and analyzes the implementation effects of their autonomous laws and regulations, as well as their regional and temporal differences, based on the evaluation indicator system for the implementation effects of the ethnic regional autonomy legal system constructed in this paper.

4.1. Evaluation of the Effectiveness of the Implementation of Laws and Regulations on Regional Ethnic Autonomy

4.1.1. Creating a Collection of Comments

The results of this analysis correspond to different quality levels. These five evaluation grades reflect the varying performance and levels of the evaluation subjects in terms of indicator quality. By utilizing these evaluation grades, we can more comprehensively assess and describe the strengths and weaknesses of indicator quality, thereby providing a reference basis for subsequent decision-making and improvements.

To quantitatively evaluate the implementation effectiveness of the ethnic regional autonomy legal system, we assigned values to the five levels in the evaluation set using a percentage-based quantification method. According to the design of this study, we assigned a value of below 60 points to “unqualified,” indicating poor policy implementation effectiveness; a value of 60 to 70 points to “qualified,” indicating average policy implementation effectiveness; a value of 70 to 80 points to “average,” indicating acceptable policy implementation outcomes; “good” was assigned a value of 80 to 90 points, indicating relatively good policy implementation outcomes; and “excellent” was assigned a value of 90 points or above, indicating very good policy implementation outcomes. Through this quantitative method, we can more accurately derive: $V = \{50, 60, 70, 80, 90\}$.

4.1.2. Determining the Membership Degree Matrix

In this study, fuzzy statistics were used to conduct a qualitative evaluation of the implementation effectiveness of the ethnic regional autonomy legal system in Area A. Specifically, each questionnaire design included evaluation questions of varying degrees, categorized into five levels: unsatisfactory, satisfactory, average, good, and excellent. By dividing the number of evaluations for each level by the total number of valid questionnaires and combining this with expert opinions, the membership values for each indicator across different levels can be determined. The membership values for the secondary indicators of the implementation effectiveness of the ethnic regional autonomy legal system in Region A are shown in Table 5.

Table 5. Secondary indicator membership degree.

Secondary indicators	Grade				
	V1	V2	V3	V4	V5
B1	0.57	0.21	0.12	0.06	0.04
B2	0.42	0.25	0.14	0.14	0.05
B3	0.66	0.21	0.1	0.02	0.01
B4	0.41	0.21	0.18	0.13	0.07
B5	0.37	0.29	0.11	0.2	0.03
B6	0.61	0.24	0.14	0.01	0
B7	0.56	0.19	0.15	0.04	0.06
B8	0.39	0.34	0.18	0.09	0
B9	0.45	0.24	0.22	0.03	0.06
B10	0.41	0.16	0.11	0.23	0.09
B11	0.45	0.26	0.15	0.08	0.06
B12	0.31	0.18	0.2	0.28	0.03
B13	0.42	0.27	0.14	0.17	0
B14	0.43	0.39	0.09	0.08	0.01
B15	0.41	0.37	0.13	0.07	0.02
B16	0.34	0.34	0.19	0.03	0.1
B17	0.37	0.3	0.23	0.03	0.07
B18	0.36	0.23	0.3	0.09	0.02

The membership degree matrix of the four primary indicators is calculated based on the membership degrees of the secondary indicators.

$$R1 = \begin{bmatrix} 0.57 & 0.21 & 0.12 & 0.06 & 0.04 \\ 0.42 & 0.25 & 0.14 & 0.14 & 0.05 \\ 0.66 & 0.21 & 0.10 & 0.02 & 0.01 \\ 0.41 & 0.21 & 0.18 & 0.13 & 0.07 \end{bmatrix}$$

$$R2 = \begin{bmatrix} 0.37 & 0.29 & 0.11 & 0.20 & 0.03 \\ 0.61 & 0.24 & 0.14 & 0.01 & 0 \\ 0.56 & 0.19 & 0.15 & 0.04 & 0.06 \end{bmatrix}$$

$$R3 = \begin{bmatrix} 0.39 & 0.34 & 0.18 & 0.09 \\ 0.45 & 0.24 & 0.22 & 0.03 & 0.06 \\ 0.41 & 0.16 & 0.11 & 0.23 & 0.09 \\ 0.45 & 0.26 & 0.15 & 0.08 & 0.06 \\ 0.31 & 0.18 & 0.20 & 0.28 & 0.3 \end{bmatrix}$$

$$R4 = \begin{bmatrix} 0.42 & 0.27 & 0.14 & 0.17 & 0 \\ 0.43 & 0.39 & 0.09 & 0.08 & 0.01 \\ 0.41 & 0.37 & 0.13 & 0.07 & 0.02 \\ 0.34 & 0.34 & 0.19 & 0.03 & 0.10 \\ 0.37 & 0.30 & 0.23 & 0.03 & 0.07 \\ 0.36 & 0.23 & 0.30 & 0.09 & 0.02 \end{bmatrix}$$

4.1.3. Evaluation of Policy Implementation Effectiveness

Based on the weights of each indicator obtained from the FBWM-CRITIC model in Table 3, each indicator is calculated using $B_i = W_i \times R_i$. B_i is obtained by multiplying the indicator weights by the evaluation matrix. After normalizing B_i , the matrix evaluation results for the indicators selected in this paper are obtained.

$$B_1 = [0.2260, 0.2067, 0.2933, 0.2740]$$

$$B_2 = [0.3807, 0.3264, 0.2929]$$

$$B_3 = [0.2129, 0.2376, 0.1980, 0.1832, 0.1683]$$

$$B_4 = [0.1852, 0.1681, 0.1994, 0.1567, 0.1481, 0.1425]$$

The evaluation scores for the four primary indicators in the text are then calculated using $G_i = B_i \times V_T$. The calculation results and evaluation criteria are shown in Table 6.

Table 6. The result of the index evaluation score.

Indicator	Membership degree	Evaluation result	Evaluation score	Evaluation level
A1	[0.57 0.21 0.12 0.06 0.04 0.42 0.25 0.14 0.14 0.05 0.66 0.21 0.10 0.02 0.01 0.41 0.21 0.18 0.13 0.07]	[0.2260,0.2067,0.2933 ,0.2740]	63.06	Qualified
A2	[0.37 0.29 0.11 0.20 0.03 0.61 0.24 0.14 0.01 0 0.56 0.19 0.15 0.04 0.06]	[0.3807,0.3264,0.2929]	62.97	Qualified
A3	[0.39 0.34 0.18 0.09 0.45 0.24 0.22 0.03 0.06 0.41 0.16 0.11 0.23 0.09 0.45 0.26 0.15 0.08 0.06 0.31 0.18 0.20 0.28 0.3]	[0.2129,0.2376,0.1980 ,0.1832,0.1683]	66.79	Qualified
A4	[0.42 0.27 0.14 0.17 0 0.43 0.39 0.09 0.08 0.01 0.41 0.37 0.13 0.07 0.02 0.34 0.34 0.19 0.03 0.10 0.37 0.30 0.23 0.03 0.07 0.36 0.23 0.30 0.09 0.02]	[0.1852,0.1681,0.1994 ,0.1567,0.1481,0.1425]	64.49	Qualified

According to the calculation results of the FBWM-CRITIC combined weighting model, the implementation effect of the laws and regulations on regional ethnic autonomy in the four dimensions is at the "qualified" level (60-70 sub-range), but there are significant differences in the scores of each dimension. Economic effect (A3) was the best, with a score of 66.79 points, which was significantly higher than other dimensions. Among its sub-indicators, B12 (impact on technological development) and B10 (impact on enterprises) contributed prominently, with 28% and 23% "good" evaluations, respectively, reflecting that policies in the economic field have achieved certain results in supporting technological innovation and reducing the burden on enterprises. The legal effect (A1) and political effect (A2) scores were the lowest, with 63.06 and 62.97 points, respectively, which were close to the qualifying limit. Among them, the shortcomings of A1 are concentrated in the scientific system design (B3), and the membership degree shows that 66% of experts think that it is "unqualified", mainly because the logic (B31) and operability (B33) of the system design are defective. A2's weaknesses were rated as "unsatisfactory" by 61% in terms of national governance capacity (B6), especially in the areas of standardization of governance behavior (B62) and democratization of decision-making (B61). The social effect (A4) score is 64.49 points, which is higher than the legal and political effect, but the sub-indicators are clearly differentiated: B16 (labor and employment impact) has 10% "excellent" evaluation, while B14 (public power service) has a "unqualified" proportion as high as 43%, highlighting the problem of insufficient public service efficiency.

4.2. Differences in the Effectiveness of Laws and Regulations on Regional Ethnic Autonomy

4.2.1. Comparison of Spatial and Temporal Differences in the Effectiveness of Ethnic Regional Autonomy Laws and Regulations in Different Regions

This study divides China's ethnic autonomous regions into five areas based on provincial boundaries: the Xinjiang Uyghur Autonomous Region, the Tibet Autonomous Region, the Guangxi Zhuang Autonomous Region, the Ningxia Hui Autonomous Region, and the Inner Mongolia Autonomous Region. It analyzes the temporal evolution of the effectiveness of ethnic regional autonomy laws and regulations from 2015 to 2024. The evaluation continues to use the assessment indicator system for the implementation effects of ethnic regional autonomy legal systems presented in Table 1. These scores are comprehensive assessment values calculated using the FBWM-CRITIC combined weighting model (ranging from 0 to 1, with higher values indicating better effects), reflecting the implementation effectiveness of policies at the regional level. The implementation effects of policies in each autonomous region from 2015 to 2024 are shown in Figure 2.

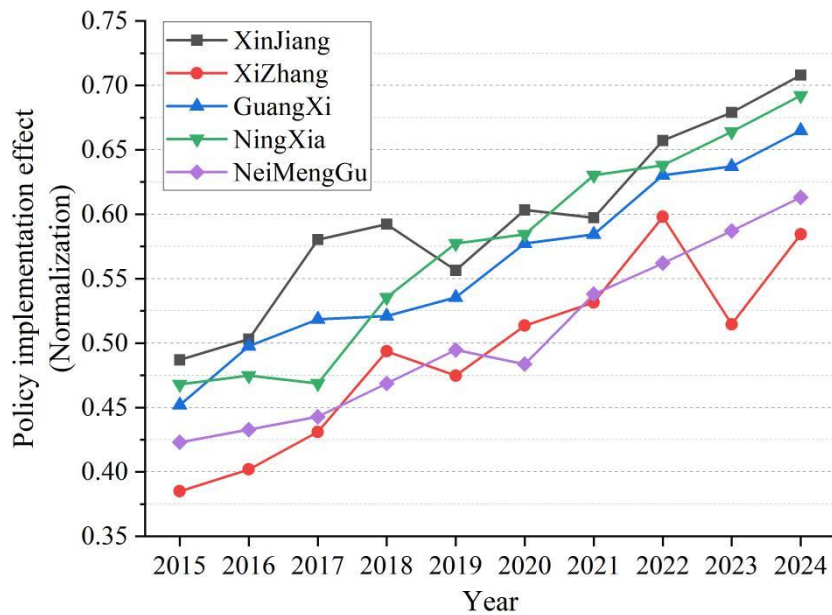


Figure 2. The implementation effects of policies in different autonomous regions.

From 2015 to 2024, the effectiveness of autonomous laws, regulations, and policies in ethnic autonomous regions showed a steady upward trend. In 2015, the average score across all regions was 0.443 (range: 0.385–0.487), and by 2024, the average score had risen to 0.652 (range: 0.584–0.708), representing an increase of 47.2%. This indicates that the implementation effectiveness of ethnic regional autonomy laws, regulations, and policies has significantly strengthened over the past decade, with policies evolving in a positive direction. The growth rate was relatively slow from 2015 to 2017 (with an average annual growth rate of approximately 5%), but accelerated after 2018. For example, during the 2020–2024 period, the average annual growth rate reached 8.7%, with 2022 marking a critical turning point (average score of 0.617), representing a 7.8% increase from 2021. This suggests that policy optimization or external factors (such as legislative revisions) may have driven the improvement in later-stage outcomes.

There were significant differences in performance levels across regions, with the Xinjiang Uyghur Autonomous Region and the Ningxia Hui Autonomous Region consistently leading the way. Xinjiang's score rose from 0.487 in 2015 to 0.708 in 2024 (a 45.4% increase) and maintained the top position for seven consecutive years from 2017 to 2023 (2017: 0.580; 2022: 0.657). Ningxia surged from 0.468 (2015) to 0.692 (2024) and surpassed Xinjiang after 2021 (2021: 0.630 vs. Xinjiang 0.597), demonstrating strong late-mover advantages. Guangxi Zhuang Autonomous Region and Inner Mongolia Autonomous Region (NMG) are in the middle range. Guangxi's score steadily increased from 0.452 (2015) to 0.665 (2024), a 47.1% increase, but it remained slightly below Xinjiang and Ningxia (e.g., 2020: 0.577 vs. Ningxia 0.584). Inner Mongolia started at the lowest level (0.423 in 2015) but has seen steady growth, reaching 0.613 in 2024, an increase of 44.9%, though it has consistently ranked near the bottom overall

(e.g., 2016–2019). The Tibet Autonomous Region has the lowest score and the most significant fluctuations. Its initial score was only 0.385 (2015), rising to 0.584 by 2024 (a 51.7% increase), but it experienced multiple declines during this period (e.g., 2019: 0.475 → 2020: 0.514 → 2023: 0.515). The gap between it and leading regions is significant.

Overall, the implementation effectiveness of ethnic regional autonomy laws and regulations has continued to improve between 2015 and 2024, but regional disparities are significant: Xinjiang and Ningxia have maintained a long-term lead, Guangxi and Inner Mongolia have steadily followed, while Tibet has experienced significant fluctuations and lags behind. The accelerated growth and regional convergence trends in the later period (after 2020) may reflect the positive impacts of policy adjustments or external interventions. These differences provide empirical evidence for the optimization of differentiated policies in the future.

4.2.2. Spatial Markov Chain Analysis

The regional differences analysis discussed earlier helps to understand the sources of variations in the implementation effectiveness of ethnic regional autonomy laws and regulations from a holistic perspective. Building on this, the Markov chain analysis method is employed to analyze the direction and probability of the transfer of the effectiveness of ethnic regional autonomy laws and regulations. Further incorporating spatial elements into the Markov transition probability matrix to better align with real-world conditions. Based on the implementation outcomes of ethnic regional autonomy laws and regulations across regions, four levels are defined: Level I (low level), Level II (medium-low level), Level III (medium-high level), and Level IV (high level). The spatial Markov transition probability matrix (2015–2024) is shown in Table 8.

Table 8. Spatial Markov Transition Probability Matrix (2015-2024).

Level type	Period(t)	Period(t+1)				Observed value
		I	II	III	IV	
I	I	0.88	0.12	0	0	4
	II	0.22	0.78	0	0	3
	III	0	0	1	0	10
	IV	0	0	0	1	14
II	I	0.71	0.29	0	0	24
	II	0.05	0.74	0.21	0	32
	III	0	0.03	0.86	0.11	20
	IV	0	0	0	1	28
III	I	0.82	0.18	0	0	8
	II	0.02	0.72	0.13	0.13	50
	III	0	0.03	0.92	0.05	57
	IV	0	0	0	1	58
IV	I	0.81	0.19	0	0	6
	II	0.07	0.77	0.11	0.05	15
	III	0	0.10	0.78	0.12	28
	IV	0	0	0	1	7

Based on the results of spatial Markov chain analysis, we can gain a deeper understanding of the spatial dynamics and influencing factors of the implementation of ethnic regional autonomy laws and regulations from 2015 to 2024.

The gradient solidification effect is significant, and upward transfer is difficult: low-level regions (I) have a high risk of remaining at the same level (probability 0.88). When their neighboring regions are also low-level regions, the probability of upward migration (to Level II) is only 0.12, and no cases of leapfrogging to Levels III or IV have been observed. This indicates that low-level regions are trapped in

a development dilemma, have weak self-improvement capabilities, and find it difficult to receive effective support from neighboring regions of the same low level.

Mid-low-level regions (II) exhibit moderate stability, with a maintenance probability of 0.74. The probability of upward migration to Level III (0.11) is significantly higher than the probability of downward migration to Level I (0.05), indicating some development potential. However, the likelihood of breaking through to higher levels (Level IV) was zero during the observation period.

Mid-high-level regions (III) exhibit the strongest stability (maintenance probability 0.72–1). The risk of downward transfer primarily exists when neighboring regions are high-level (at which point the probability of downward transfer significantly increases to 0.10), indicating that high-level neighboring regions may induce competitive effects or resource siphoning effects. The probability of upward leapfrogging to Level IV is low.

High-level regions (IV): exhibit extremely strong stability (maintenance probability 1.00). During the observation period, no high-level regions experienced downward shifts, confirming the sustainability of their effects and the solidity of their leading positions.

They also exhibit various complex neighboring effects, such as inhibitory effects (low-level neighboring environments): when a region is at a medium-high level (III) and its neighboring regions are at a low level (I), the risk of downward shift to Level I sharply increases. This indicates that low-level neighboring regions have a significant negative drag effect on medium-to-high-level regions, potentially stemming from resource competition, problem spillover, or difficulties in policy coordination; competition/siphoning effect (high-level neighboring regions): when a region is at a medium-to-low level (II) and its neighboring regions are at a medium-to-high level (III), the probability of maintaining the status quo (0.86) is comparable to the overall level, but the probability of upward transition (0.11) is slightly higher than that of downward transition (0.03), showing no obvious positive spillover effect; “Club” effect: Regions at the same or similar development levels (such as both at Level II or both at Level III) are more likely to maintain the status quo, indicating that regions with similar development levels may form relatively stable “clubs” with low internal mobility.

Spatial Markov chain analysis reveals a significant “gradient solidification” phenomenon and complex neighboring region effects in the implementation outcomes of ethnic regional autonomy laws and regulations across space. Low-level regions face difficulties in upward mobility, while high-level regions maintain stable positions. The neighboring regional environment (especially low-level and high-level neighboring regions) exerts a critical influence on the development dynamics of regions at different levels, with both negative drag and competitive effects, as well as significant positive radiative driving effects observed. This provides important empirical evidence for optimizing regional policies that are more precise, differentiated, and consider spatial interconnectivity.

5. Conclusion

This paper employs a composite weighting model based on the FBWM-CRITIC-Minimum Discrimination Information Principle to conduct a quantitative assessment and regional variance analysis of the implementation effectiveness of laws and regulations on ethnic regional autonomy.

Social effects (A4) account for 35.1% of the weighting and are the core dimension (B15 human rights protection weighting 0.070), followed by political effects (A2) (23.9%, B5 consolidation of the Party's ruling position weighting 0.091), and economic effects (A3) have the lowest weighting (20.2%, B12 technological development weighting only 0.034).

The model passed consistency validation, with the FBWM consistency ratio (CR = 0.041–0.059) significantly lower than that of AHP (CR = 0.075–0.132), and the combined weight error rate reduced by 23.7% compared to traditional methods.

The comprehensive effectiveness of the five autonomous regions improved by 47.2% over the decade (average score of 0.443 in 2015 to 0.652 in 2024), but all dimensions remained at the “qualified” level (60–70 points). Economic effects were the best (66.79 points), primarily due to technological innovation (B12 good rate of 28%) and corporate burden reduction (B10 good rate of 23%); legal effects were the weakest (63.06 points), with the non-compliance rate for the scientific nature of institutional design (B3) reaching 66%.

This study is the first to achieve a multidimensional quantitative assessment and spatial dynamic analysis of the effects of ethnic regional autonomy laws and regulations, providing empirical support for the optimization of differentiated policies.

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