

A Game-Theoretic and Double-Frontier DEA Approach with Combined Weighting for Evaluating Converged Media Centers

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ABSTRACT

In the context of media convergence, evaluating the construction effectiveness of converged media centers has become crucial. Taking the converged media center as the research object, this paper divides the evaluation into three dimensions: institutional construction evaluation (input perspective), convergence effect evaluation (output perspective), and operational efficiency evaluation (input-output relationship). The respective index systems for institutional construction and convergence effect are established, and a comprehensive evaluation algorithm integrating subjective and objective assessments is proposed. A depersonalized AHP method is designed to optimize subjective weights, the CRITIC method is employed to calculate objective weights, and game theory is applied to combine them, yielding comprehensive evaluation weights. Based on corresponding indicator data, the evaluation results for institutional construction and convergence effect are obtained. For operational efficiency, an evaluation model based on double-frontier stochastic DEA is proposed, with input and output indicators being the first-level indicators of the two systems. Optimal efficiency and worst efficiency are calculated from the optimal and worst frontiers, respectively, and unified via the geometric mean method to obtain comprehensive efficiency. Compared with traditional DEA, this method effectively distinguishes the relative efficiency among decision-making units with an efficiency of 1. Pearson correlation test results of comprehensive efficiency values under different risk levels show a strong positive correlation, indicating the model's feasibility and stability. Finally, a case study of 36 converged media centers verifies the applicability of the proposed evaluation method, providing a new approach for the assessment of converged media centers.

INTRODUCTION

The converged media center (CMC) is a concept with Chinese characteristics. It is an organization that takes the Internet as the platform, information technology as the support, new media as the direction, integration and innovation as the means, public opinion guidance as the main responsibility, and serving the people as the purpose. In the context of media convergence, the construction of county-level converged media centers in China has developed rapidly in recent years, but it remains in a state of trial and exploration. Therefore, scientifically and effectively measuring the construction and practical performance of county-level converged media centers has become a crucial research problem.

Existing research has primarily focused on social media evaluation. Peng S et al. (2018) provided a comprehensive overview of social networks. Wouters P, et al. (2019) discussed the application of social media indicators in scientific evaluation. Kothari H, et al. (2025) examined the impact of social media advertising on consumer behavior.

Sančanin B, et al. (2024) applied Fuzzy AHP and PCA to analyze media influence on education and labor markets. Song J, et al. addressed dual-task optimization for influencer recommendation, and Song J, et al. (2024) developed a data-driven model for short-video communication.

Regarding evaluation methodologies, Multi-Criteria Decision-Making (MCDM) approaches have been widely adopted. Saaty TL established the fundamental principles of AHP. Sun CC. (2010) integrated Fuzzy AHP and Fuzzy TOPSIS for performance evaluation. Li H, et al. (2021) conducted a multi-criteria analysis using integrated Fuzzy AHP and DEA. Tran NT, et al. (2024) applied Fuzzy AHP-TOPSIS for robot selection, and Saboor S, et al. (2025) developed a hybrid AHP-Fuzzy MOORA for social sustainability assessment. For specific contexts, Tamimu MG, et al. (2025) used Pythagorean Fuzzy AHP for digital trade risk evaluation. Mladenović M, et al. (2025) employed Fuzzy AHP for rural sustainable development.

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Keywords: Convergence media center; Index system; Combined weighting; Efficiency evaluation.

Özkurt P. (2026) developed a robust intuitionistic Fuzzy AHP-TOPSIS model for healthcare waste treatment. Regarding weighting, Wang Y et al. (2025) proposed an AHP-CRITIC framework to reduce evaluation noise. Zheng W et al. (2024) developed a game theory-based fuzzy evaluation method for tunnel collapse risk. Zou C et al. (2025) introduced fuzzy geometric operators for teaching quality evaluation.

In efficiency evaluation, Data Envelopment Analysis (DEA) and its extensions have been extensively utilized. The classic DEA model was pioneered by Charnes, Cooper, and Rhodes E, et al. (1978). Tone K. (2001) introduced the Slacks-Based Measure (SBM). Guo P, et al. (2001) proposed Fuzzy DEA as a perceptual evaluation method. Nguyen and O'Donnell C, et al. (2025) explored alternative frontiers via Stochastic Frontier Analysis (SFA). Arabmaldar A, et al. (2026) developed robust DEA models with new uncertainty sets. Deng Q. (2024) proposed an OCBA-AIC method for stochastic variable selection in DEA. Aparicio J, et al. (2026) introduced machine learning-enhanced production frontier estimation. In applications, Wang K, et al. (2026) applied slacks-based network DEA to national logistics performance. Sun J, et al. (2024) evaluated pharmaceutical companies using three-stage DEA with undesirable outputs. Recent studies have further extended the methodology to complex frontier settings. Saen R F, et al. (2025) explored non-convex double frontiers in sustainable transportation supply chains. Izadikhah M, et al. (2026) proposed a fuzzy-stochastic DEA approach for benchmarking top-performing companies. Jahani Sayyad Noveiri M, et al. (2025) assessed circular economy performance using double-frontier multi-period DEA with flexible measures.

Most existing studies focus on a single evaluation problem, with obvious deficiencies in multidimensional evaluation methods. This study takes the converged media center as the evaluation object, designs a fusion evaluation method based on existing research, and realizes evaluation from three dimensions: institutional construction, fusion effect, and operational efficiency.

MATERIALS AND METHODS

The Establishment of Evaluation Index Systems

Institutional Construction Evaluation Index System

The institutional construction evaluation measures the level of resource input and foundational support within county-level converged media centers. By deconstructing institutional development into multiple dimensions, this study establishes a three-pillar framework to serve as input variables for efficiency analysis

- **Organization Construction:** As the primary guarantee for institutional development, this dimension covers talent construction and institutional mechanisms. The former

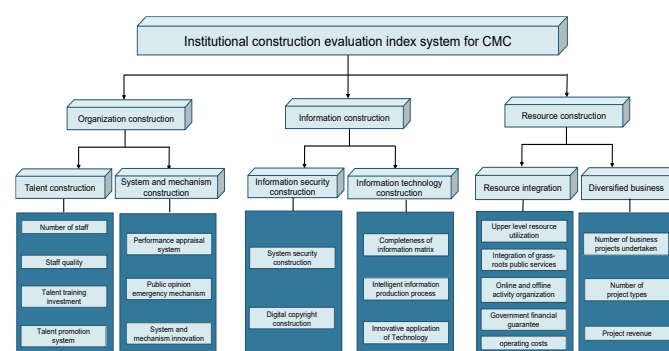
emphasizes staff scale, quality, and training investment, while the latter focuses on performance appraisal, public opinion emergencies, and innovation mechanisms.

- **Information Construction:** This reflects the technical support capabilities of the center, encompassing information security and information technology application. It includes system protection, digital copyright, media matrix completeness, intelligent processes, and technical innovation.

- **Resource Construction:** This measures the support for sustainable development by assessing resource acquisition and self-sustaining capacity through resource integration and diversified business, including utilization of superior resources, grassroots service integration, fiscal guarantees, and revenue from market-oriented projects.

The hierarchical structure of this system is illustrated in Figure 1.

Figure 1: Hierarchy chart of organization construction evaluation index system



Fusion Effect Evaluation Index System for Cmc

The fusion effect index system quantifies the communication output and social impact of converged media centers. Drawing on relevant literature, this study develops a comprehensive model with four core dimensions to serve as output variables for efficiency analysis:

- **Propagation Force:** Serving as the foundation for guidance and influence, this encompasses sustainable propagation and radiation propagation. The former focuses on the volume of articles and videos produced, while the latter addresses the follower scale across various platforms.

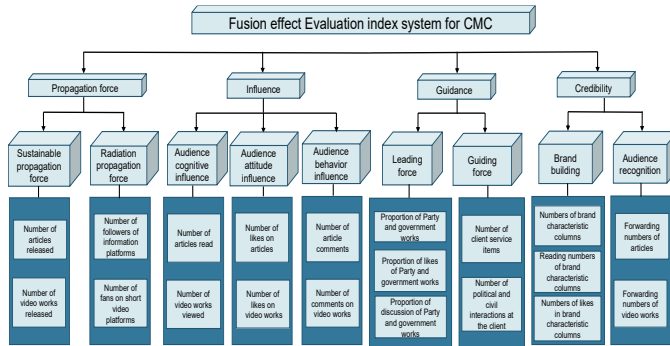
- **Influence:** Following the logic of cognition, attitude, and behavior, this assesses the actual impact of communication content on audiences through the synthesis of reads, views, likes, and comments for both articles and videos.

- **Guidance:** This represents the effectiveness of public opinion guidance, including leading force and guiding force. It involves the proportion and engagement of government-related works, the provision of client service items, and political-civil interactions.

• **Credibility:** Reflecting the intrinsic power to gain public trust, this is evaluated through brand building and audience recognition. Specific focus is placed on the performance of characteristic columns, content forwarding, and secondary dissemination.

The detailed logical framework is presented in Figure 2

Figure 2: Hierarchical chart of fusion effect evaluation index system



Game Theory Combined Weighting Algorithm

Subjective Weight Algorithm

After determining the hierarchical structure of the evaluation index system, this paper adopts the AHP method to calculate the weights of each indicator. To reduce the interference of individual experts' subjective preferences, a depersonalized AHP algorithm is introduced using nonlinear optimization modeling. The specific steps are as follows:

• Step 1: Construct the judgment matrix

A group of n experts compares the importance of m indicators at the same hierarchy. For the i -th expert, the judgment matrix $A^{(i)} = (a_{ij}^{(i)})_{m \times m}$ is constructed using Saaty's 1–9 scale Saaty TL.

$$A = [a_{ij}]_{m \times m} = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mm} \end{bmatrix} \quad (1)$$

Where $a_{ij}^{(i)} > 0, a_{ij}^{(i)} = 1/a_{ji}^{(i)}$ and $a_{ii}^{(i)} = 1$.

• Step 2: Calculate initial weights and consistency check

The initial weight vector $p_i = (p_1, p_2, \dots, p_m)^T$ is calculated using the geometric mean method. First, compute p_i :

$$p_i = \sqrt[m]{\prod_{j=1}^m a_{ij}} \quad (i = 1, 2, \dots, m) \quad (2)$$

Then normalize to obtain the weights:

$$b_i = \frac{p_i}{\sum p_i} \quad (i = 1, 2, \dots, m) \quad (3)$$

The maximum eigenvalue $\lambda_{\max}$ is calculated as:

$$\lambda_{\max} = \frac{\sum_{i=1}^m \sum_{j=1}^m a_{ij} b_i}{\sum p_i} \quad (4)$$

The consistency index CI and consistency ratio CR are:

$$CI = \frac{\lambda_{\max} - m}{m - 1}, \quad CR = \frac{CI}{RI} \quad (5)$$

Where RI is the average random consistency index Yan M, et al. (2026). The matrix is acceptable only when $CR < 0.10$.

• Step 3: Construct the expert evaluation matrix

For n experts and m indicators, the expert evaluation matrix X is:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad (6)$$

Where x_{ij} the AHP weight given by the i -th expert for the j -th indicator.

• Step 4: Calculate the perceptual correlation coefficient

The perceptual correlation coefficient r_{ij} between expert i and expert j is:

$$r_{ij} = \frac{x_i x_j^T}{\|x_i\| \|x_j\|} \quad (7)$$

Where x_i is the i -th row vector of X . The net perceptual coefficient c_{ij} is:

$$c_{ij} = r_{ij} - (1 - r_{ij}) = 2r_{ij} - 1 \quad (8)$$

• Step 5: Solve the group preference weight model.

The optimization model for solving the group preference weight vector is:

$$\max \sum_{i=1}^m [\mathbf{y} \mathbf{y}^{(i)T}]^2, \text{ s.t. } \|\mathbf{y}\|_2 = 1 \quad (9)$$

Where $\mathbf{y} \mathbf{y}^{(i)T} = (y_1^{(i)}, y_2^{(i)}, \dots, y_n^{(i)})^T$ and $y_k^{(i)} = \sum_{j=1}^m x_{kj} y_j^{(i)*}$.

• Step 6: Calculate the depersonalized AHP subjective weight

The final depersonalized subjective weight vector $M_i = [M_1, M_2, \dots, M_m]$ is:

$$M_i = \sum_{k=1}^n y_k^* x_{ki}, i = 1, 2, \dots, m \quad (10)$$

Where y_k^* is the optimized expert weight from Step 5.

Objective Weight Algorithm

This paper employs the CRITIC method Yan M, et al. (2026) to calculate the objective weights of evaluation indicators. This method determines weights by integrating the contrast intensity and conflict of each indicator. The calculation steps are as follows:

• Step 1: Data standardization

Suppose n data samples are collected for m evaluation indicators. The original data matrix is $X = [x_{ij}]_{n \times m}$:

$$X = [x_{ij}]_{n \times m} = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \quad (11)$$

To eliminate the effect of different dimensions, the indicators are normalized using min-max normalization:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}, i = 1, 2, \dots, n; j = 1, 2, \dots, m. \quad (12)$$

• Step 2: Calculate contrast intensity and conflict

The contrast intensity of the j -th indicator is measured by its standard deviation:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^n (x'_{ij} - \bar{x}'_j)^2}{n-1}} \quad (13)$$

The conflict of the j -th indicator with others is measured by the sum of correlation coefficients

$$f_j = \sum_{i=1}^m (1 - r_{ij}) \quad (14)$$

Where r_{ij} is the Pearson correlation coefficient between the ij -th and j -th indicators.

• Step 3: Calculate information carrying capacity and objective weights

The information carrying capacity C_j of the j -th indicator is the product of contrast intensity and conflict:

$$C_j = \sigma_j f_j \quad (15)$$

The objective weight ω_j of the j -th indicator is obtained by normalizing C_j :

$$\omega_j = \frac{C_j}{\sum_{j=1}^m C_j} \quad (16)$$

The resulting objective weight vector is denoted as $W = (\omega_1, \omega_2, \dots, \omega_m)$.

Game Theory Combined Weighting Algorithm

To find the consistency or compromise between subjective and objective weights, this study introduces game theory combined weighting. The subjective weight vector $M = [M_1, M_2, \dots, M_m]$ is obtained by the depersonalized AHP method, and the objective weight vector $W = [w_1, w_2, \dots, w_m]$ is obtained by the CRITIC method. The game theory approach seeks to minimize the deviation between the combined weights and each individual weight vector.

• Step 1: Construct the cross-programming model

The optimal combined weight vector is obtained by solving the following optimization model:

$$\begin{aligned} \min & (\|\alpha_1 M + \alpha_2 W - M\|_2 + \|\alpha_1 M + \alpha_2 W - W\|_2) \\ \text{s.t.} & \alpha_1 + \alpha_2 = 1, \alpha_1, \alpha_2 \geq 0 \end{aligned} \quad (17)$$

Where α_1 and α_2 are the weight coefficients to be determined.

• Step2: Solve for the optimal coefficients

Using the first derivative condition of the optimization model, the following equations are obtained:

$$\begin{aligned} \alpha_1 MM^T + \alpha_2 MW^T &= MM^T \\ \alpha_1 WM^T + \alpha_2 WW^T &= WW^T \end{aligned} \quad (18)$$

These equations can be written in matrix form:

$$\begin{bmatrix} MM^T & MW^T \\ WM^T & WW^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} MM^T \\ WW^T \end{bmatrix} \quad (19)$$

Solving equation 19 yields the optimal coefficients α_1 and α_2 .

• Step 3: Calculate the combined weights

The combined subjective and objective weight vector G is calculated as:

$$G = \alpha_1 M + \alpha_2 W \quad (20)$$

The final evaluation result vector is then obtained by:

$$Result = G' X^T \quad (21)$$

Where X is the standardized evaluation index data matrix.

Efficiency Evaluation Model Based on Double Frontier Stochastic DEA

Through the first two sections, this paper constructs the institutional construction and fusion effect evaluation index systems for CMC from input and output perspectives, and proposes a combined weighting algorithm.

The three first-level indicators of institutional construction (organization, information, resource) are taken as three input random variables; the four first-level indicators of fusion effect (propagation force, influence, guidance, credibility) are taken as four output random variables. Using the statistical characteristics of input-output data of each DMU, the optimal efficiency and worst efficiency are calculated from the optimal frontier and worst frontier, respectively. Finally, the geometric mean method unifies them to obtain the comprehensive efficiency of each DMU.

Stochastic DEA Efficiency Evaluation Model Based on The Optimal Frontier

The efficiency determined by the optimal frontier is ≤ 1 . By comparing each DMU with the best-performing DMU on the optimal frontier, the optimal efficiency of each DMU is obtained. Assuming n DMU s with m inputs and s outputs, the stochastic DEA model based on the optimal frontier is shown in equation 22, where DMU_0 is the unit under evaluation:

$$\begin{aligned} BE_o^{\alpha*} = \min \frac{\theta_o^{\alpha}}{\varphi_o^{\alpha}} - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ s.t. \ p \left\{ \sum_{j=1}^n \lambda_j \tilde{x}_{ij} + s_i^- \leq \theta_o^{\alpha} \tilde{x}_{io} \right\} \geq 1 - \alpha, i = 1, 2, \dots, m, \\ p \left\{ \sum_{j=1}^n \lambda_j \tilde{y}_{rj} - s_r^+ \geq \varphi_o^{\alpha} \tilde{y}_{ro} \right\} \geq 1 - \alpha, r = 1, 2, \dots, s, \\ \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, 2, \dots, n, \theta_o^{\alpha} \geq 0, \varphi_o^{\alpha} \geq 0. \end{aligned} \quad (22)$$

Following Cooper WW, et al. (2002), its deterministic equivalent form is shown in equation 23:

$$\begin{aligned} BE_o^{\alpha*} = \min \frac{\theta_o^{\alpha}}{\varphi_o^{\alpha}} - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ s.t. \ \sum_{j=1}^n \lambda_j x_{ij} - \theta_o^{\alpha} x_{io} + s_i^- - \phi^{-1}(\alpha) \sigma_i^I(\theta_o^{\alpha}, \lambda) = 0, i = 1, 2, \dots, m, \\ \sum_{j=1}^n \lambda_j y_{rj} - \varphi_o^{\alpha} y_{ro} - s_r^+ + \phi^{-1}(\alpha) \sigma_r^O(\varphi_o^{\alpha}, \lambda) = 0, r = 1, 2, \dots, s, \\ \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, 2, \dots, n, \theta_o^{\alpha} \geq 0, \varphi_o^{\alpha} \geq 0. \end{aligned} \quad (23)$$

The $BE_o^{\alpha*}$ obtained is optimal efficiency of DMU_o .

Stochastic DEA Efficiency Evaluation Model Based on The Worst Frontier

The efficiency determined by the worst frontier is ≥ 1 . By comparing each DMU with the worst-performing DMU on the worst frontier, the worst efficiency of each DMU is

obtained. For DMU_o , the model is shown in equation 24:

$$\begin{aligned} WE_o^{\alpha*} = \max \frac{\theta_o^{\alpha}}{\varphi_o^{\alpha}} + \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ s.t. \ p \left\{ \sum_{j=1}^n \lambda_j \tilde{x}_{ij} - s_i^- \geq \theta_o^{\alpha} \tilde{x}_{io} \right\} \geq 1 - \alpha, i = 1, 2, \dots, m, \\ p \left\{ \sum_{j=1}^n \lambda_j \tilde{y}_{rj} + s_r^+ \leq \varphi_o^{\alpha} \tilde{y}_{ro} \right\} \geq 1 - \alpha, r = 1, 2, \dots, s, \\ \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, 2, \dots, n, \theta_o^{\alpha} \geq 0, \varphi_o^{\alpha} \geq 0. \end{aligned} \quad (24)$$

Following Cooper WW, et al. (2002), its deterministic equivalent form is shown in equation 25:

$$\begin{aligned} WE_o^{\alpha*} = \max \frac{\theta_o^{\alpha}}{\varphi_o^{\alpha}} + \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ s.t. \ \sum_{j=1}^n \lambda_j x_{ij} - \theta_o^{\alpha} x_{io} - s_i^- + \phi^{-1}(\alpha) \sigma_i^I(\theta_o^{\alpha}, \lambda) = 0, i = 1, 2, \dots, m, \\ \sum_{j=1}^n \lambda_j y_{rj} - \varphi_o^{\alpha} y_{ro} + s_r^+ - \phi^{-1}(\alpha) \sigma_r^O(\varphi_o^{\alpha}, \lambda) = 0, r = 1, 2, \dots, s, \\ \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0, j = 1, 2, \dots, n, \theta_o^{\alpha} \geq 0, \varphi_o^{\alpha} \geq 0. \end{aligned} \quad (25)$$

The $WE_o^{\alpha*}$ obtained is the worst efficiency of DMU_o .

Synthesis Of Double Frontier Stochastic DEA Efficiency Based on The Geometric Mean Method

At risk level α , the optimal efficiency $BE_j^{\alpha*}$ and worst efficiency $WE_j^{\alpha*}$ of each DMU are obtained. The geometric mean method unifies them to obtain the comprehensive efficiency of DMU_o , as shown in equation 26:

$$CE_j^{\alpha*} = \sqrt{BE_j^{\alpha*} \times WE_j^{\alpha*}}, j = 1, 2, \dots, n \quad (26)$$

Where $CE_j^{\alpha*}$ is the comprehensive efficiency of the j -th DMU.

RESULTS & DISCUSSION

Selection Of Evaluation Objects

Through cooperation with 36 CMCs in Shanxi, Hebei and Inner Mongolia in North China, Jiangsu, Zhejiang, Fujian, Jiangxi and Shandong in East China, Hubei and Hunan in Central China, Guangdong and Guangxi in South China, Jilin and Liaoning in Northeast China, Shaanxi, Gansu, Ningxia and Xinjiang in Northwest China, Sichuan, Guizhou, Chongqing, Yunnan in Southwest China, the 36 CMCs are taken as the empirical research evaluation objects of this study. For convenience, the 36 CMCs are represented by C1–C36. Table 1 shows the corresponding relationship between the names and pronouns of the 36 CMCs. According to the evaluation index system constructed, first-hand index data were obtained from the 36 CMCs.

Table 1: The corresponding relationship between CMCs and pronouns

CMC	Province	Pronoun	CMC	Province	Pronoun
Gujiao	Shanxi	C1	Hengyang	Hunan	C19
Qingxu	Shanxi	C2	Longgang District	Guangdong	C20
Yuncheng	Shanxi	C3	Dongguan	Guangdong	C21
Yangcheng	Shanxi	C4	Hengxian	Guangxi	C22
Houma	Shanxi	C5	Changchun	Jilin	C23
Wu'an	Hebei	C6	Wafangdian	Liaoning	C24
Shenzhou	Hebei	C7	Donggang	Liaoning	C25
Bahrain Zuoqi	Inner Mongolia	C8	Lantian	Shaanxi	C26
Guanyun	Jiangsu	C9	Zichang	Shaanxi	C27
Shuyang	Jiangsu	C10	Guazhou	Gansu	C28
Yongjia	Zhejiang	C11	Zhongning	Ningxia	C29
Jiangle County	Fujian	C12	Aksu	Xinjiang	C30
Fenyi	Jiangxi	C13	Gaoping District	Sichuan	C31
Rencheng District	Shandong	C14	Chaotian District	Sichuan	C32
Wulian	Shandong	C15	Zheng'an	Guizhou	C33
Pingdu	Shandong	C16	Qiandongnan	Guizhou	C34
Xinzhou District	Hubei	C17	Jiangjin District	Chongqing	C35
Xiangzhou District	Hubei	C18	Chuxiong	Yunnan	C36

Institutional construction evaluation

The subjective weight results of depersonalized AHP in institutional construction evaluation are shown in Table 2. The three-level indicators with large subjective weight are system security construction (i211), performance appraisal system (i121), staff quality (i112) and public

opinion emergency mechanism (i122). Thus, in the institutional construction evaluation of CMCs, the subjective method pays more attention to system security, talent team quality, and public opinion handling capability.

The objective weight results calculated by the CRITIC method are shown in Table 3.

Table 2: Subjective weight results in institutional construction evaluation

index	i111	i112	i113	i114	i121
Subjective weight	0.03162463	0.07292253	0.06635727	0.06827298	0.08934896
index	i122	i123	i211	i212	i221
Subjective weight	0.07241218	0.06353489	0.1139488	0.04551482	0.05175825
index	i222	i223	i311	i312	i313
Subjective weight	0.03300812	0.02834538	0.03546707	0.02430884	0.02636938
index	i314	i315	i321	i322	i323
Subjective weight	0.02387917	0.02659219	0.039778	0.02470593	0.06186215

Table 3: Objective weight results in institutional construction evaluation

index	i111	i112	i113	i114	i121
Objective weight	0.05108037	0.0466074	0.05315047	0.04579498	0.03874471
index	i122	i123	i211	i212	i221
Objective weight	0.05328598	0.05709514	0.06527894	0.04598815	0.02994585
index	i222	i223	i311	i312	i313
Objective weight	0.0456897	0.05554404	0.07573436	0.04723694	0.04396456
index	i314	i315	i321	i322	i323
Objective weight	0.04825079	0.03809898	0.06232986	0.05255732	0.04362148

The objective weights, which consider both variability and correlation of the indexes, overcome the serious polarization of index weight distribution, proving that the objective weights determined by the CRITIC method are reliable and reasonable. The comprehensive evaluation weights of institutional construction obtained by the game theory combined weighting method are shown in Table 4, and 0.88519665,

$$\alpha_2 = 0.14144575.$$

By aggregating the weights of the three-level indicators, the corresponding comprehensive evaluation weights of the second-level and first-level indicators are obtained, as shown in Table 5. For institutional construction, most important, with a comprehensive

Table 4: Comprehensive evaluation weight results in institutional construction evaluation

index	i111	i112	i113	i114	i121
Comprehensive evaluation weight	0.03430481	0.06929627	0.06453706	0.065175	0.082376
index	i122	i123	i211	i212	i221
Comprehensive evaluation weight	0.06977638	0.06264703	0.10724224	0.04558	0.048753
index	i222	i223	i311	i312	i313
Comprehensive evaluation weight	0.03475498	0.03209235	0.04101449	0.027467	0.028793
index	i314	i315	i321	i322	i323
Comprehensive evaluation weight	0.0272367	0.02817726	0.04288466	0.028543	0.059348

Table 5: Comprehensive evaluation weight results of the first-level and second-level indicators of institutional construction evaluation index system

first-level indicators	weights	second-level indicators	weights
Organization construction(i1)	0.4481131	Talent construction(i11)	0.23331356
		System and mechanism construction(i12)	0.21479954
Information construction(i2)	0.26842171	Information security construction(i21)	0.15282182
		Information technology construction(i22)	0.11559989
Resource construction(i3)	0.28346519	Resource integration(i31)	0.15268921
		Diversified business(i32)	0.13077598

weight of 0.4481131. Resource construction (0.28346519) is slightly organization construction is the more important than information construction (0.26842171).

The institutional construction evaluation results of the 36 CMCs are shown in Table 6.

Table 6. Institutional construction evaluation results of 36 CMCs

region	CMC	result	ranking	region	CMC	result	ranking
North China	C1	0.24449902	34	South China	C20	0.61094328	8
	C2	0.37686705	28		C21	0.55102074	10
	C3	0.45019516	22		C22	0.47162973	16
	C4	0.50762762	13	Northeast China	C23	0.81170601	1
	C5	0.34540144	30		C24	0.6551346	4
	C6	0.52506657	11		C25	0.5003124	14
	C7	0.45647632	20	Northwest China	C26	0.51039108	12
	C8	0.1998437	36		C27	0.4358214	23
East China	C9	0.25372367	33		C28	0.47147894	17
	C10	0.36900659	29	Southwest China	C29	0.33433128	31
	C11	0.74229922	3		C30	0.49948195	15
	C12	0.40752213	27		C31	0.6191989	6
	C13	0.64084371	5		C32	0.61469943	7
	C14	0.57099676	9		C33	0.20779232	35
	C15	0.41985212	24		C34	0.46289893	19
	C16	0.41547666	25		C35	0.80489289	2
Central China	C17	0.41363858	26		C36	0.2755241	32
	C18	0.4644316	18				
	C19	0.45159383	21				

Fusion Effect Evaluation

Table 7 shows the subjective weights (depersonalized AHP), objective weights (CRITIC), and comprehensive evaluation weights (game theory combined weighting) for the fusion effect evaluation.

Indicators with large subjective weight are number of followers of information platform (o121), number of client service items (o321), and number of fans on short video platform (o122). Thus, the subjective evaluation method focuses more on audience scale and comprehensive service capability.

The objective weights determined by CRITIC consider both variability and correlation of the index data effectively. The comprehensive evaluation weights fully reflect the consistency or compromise between subjective and objective weights, with no extreme phenomenon of a single index dominating the overall weight, demonstrating the rationality and effectiveness of the indicators and weights. The game theory combined weighting yields

$$\alpha_1 = 0.8406149, \alpha_2 = 0.20181772.$$

By aggregating the weights of the three-level indicators, the corresponding comprehensive evaluation weights of the second-level and first-level indicators are obtained, as shown in Table 8.

For the fusion effect, propagation force (o1) has the highest weight (0.29829134), followed by credibility (o4) at 0.25174887, guidance (o3) at 0.24084019, and influence (o2) at 0.2091196.

The fusion effect evaluation results of 36 CMCs can be obtained by weighted summation of the fusion effect evaluation index data and the corresponding comprehensive evaluation weights. The fusion effect evaluation results of 36 CMCs are shown in Table 9.

Operational Efficiency Evaluation

The three first-level indicators of institutional construction (organization construction i1, information construction i2, resource construction i3) are taken as the three input random variables and the four first-level indicators of fusion effect

Table 7: Comparison of subjective weight, objective weight, and comprehensive evaluation weight results of three-level indicators for fusion effect evaluation

Fusion effect evaluation index	Subjective weight	Objective weight	Comprehensive evaluation weight
Number of articles released(o111)	0.06026914	0.07234162	0.06260536
Number of video works released(o112)	0.05388564	0.0565912	0.05440854
Number of followers of information platforms(o121)	0.11034732	0.04582971	0.09785491
Number of fans on short video platforms(o122)	0.09397109	0.03949269	0.08342253
Number of articles read(o211)	0.02231923	0.04536196	0.02677992
Number of video works viewed(o212)	0.03775797	0.04038964	0.03826683
Number of likes on articles(o221)	0.02574051	0.04664272	0.02978674
Number of likes on video works(o222)	0.03613641	0.04362518	0.03758563
Number of article comments(o231)	0.02455266	0.05240059	0.02994359
Number of comments on video works(o232)	0.04780316	0.04240297	0.04675689
Proportion of Party and government works(o311)	0.03126808	0.05912818	0.03666126
Proportion of likes of Party and government works(o312)	0.03096694	0.05827476	0.0362532
Proportion of discussion of Party and government works(o313)	0.03238759	0.07247763	0.04014847
Number of client service items(o321)	0.10025584	0.04749867	0.09004041
Number of political and civil interactions at the client(o322)	0.03619008	0.04418274	0.03773685
Numbers of brand characteristic columns(o411)	0.04835101	0.04680011	0.04804995
Reading numbers of brand characteristic columns(o412)	0.03415576	0.04120715	0.03552034
Numbers of likes in brand characteristic columns(o413)	0.05136931	0.0550406	0.05207922
Forwarding numbers of articles(o421)	0.06043663	0.03998105	0.05647544
Forwarding numbers of video works(o422)	0.06185627	0.05033081	0.05962392

Table 8: Comprehensive evaluation weight results of the first-level and second-level indicators of fusion effect evaluation

first-level indicators	weights	second-level indicators	weights
Propagation force(o1)	0.29829134	Sustainable propagation force(o11)	0.1170139
		Radiation propagation force(o12)	0.18127744
Influence(o2)	0.2091196	Audience cognitive influence(o21)	0.06504675
		Audience attitude influence(o22)	0.06737237
		Audience behavior influence(o23)	0.07670048
Guidance(o3)	0.24084019	Leading force(o31)	0.11306293
		Guiding force(o32)	0.12777726
Credibility(o4)	0.25174887	Brand building(o41)	0.13564951
		Audience recognition(o42)	0.11609936

Table 9: Fusion effect evaluation results of 36 CMCs

region	CMC	result	ranking	region	CMC	result	ranking
North China	C1	0.06072962	34	South China	C20	0.31792349	6
	C2	0.15813875	13		C21	0.41181067	2
	C3	0.08540808	29		C22	0.15189355	14
	C4	0.10022282	26	Northeast China	C23	0.21446291	9
	C5	0.18276833	11		C24	0.10710645	23
	C6	0.13240353	19		C25	0.12461355	20
	C7	0.08880646	28	Northwest China	C26	0.21855637	8
	C8	0.11716401	22		C27	0.10470781	25
East China	C9	0.13476308	17		C28	0.12442289	21
	C10	0.08164391	31	Southwest China	C29	0.14906243	15
	C11	0.18636981	10		C30	0.10709059	24
	C12	0.13941762	16		C31	0.08350359	30
	C13	0.28721746	7		C32	0.03872264	36
	C14	0.06407485	33		C33	0.08133101	32
	C15	0.4177659	1		C34	0.15929536	12
	C16	0.33682565	4		C35	0.3403198	3
Central China	C17	0.32099771	5		C36	0.04356346	35
	C18	0.13256372	18				
	C19	0.09720279	27				

(propagation force o1, influence o2, guidance o3, credibility o4) are taken as the four output random variables. Using the corresponding index data of the 36 CMCs collected in 2020, the input-output data for the 36 DMUs (C1–C36) are generated. For each DMU, the weighted sum of the three-level indicator data under each first-level indicator and the corresponding comprehensive evaluation weight yields the input-output data set as the mean of the random variables. Due to the limited development time of CMCs, obtaining a large number of data samples is difficult. Therefore, this study uses 15% of the mean to generate the standard deviation as the error range. Following existing stochastic DEA

research Cooper WW, et al. (2002), Yan M, et al. (2026), Jahani Sayyad Noveiri M, et al. (2021), it is assumed that the random variables of input and output indicators follow a normal distribution. Under different risk levels $\alpha=0.4, 0.5, 0.7$, the software GAMS is used to model and solve the comprehensive efficiency. The results are shown in Table 10.

Analysis of Institutional Construction Evaluation Results

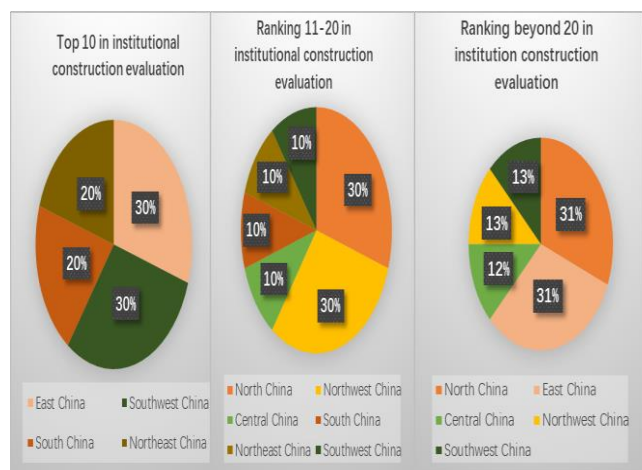
Among all evaluation samples, the top three CMCs in the institutional construction evaluation results are Changchun (C23) in Northeast China, Jiangjin (C35) in Southwest China, and Yongjia (C11) in East China.

Table 10: Comprehensive efficiency evaluation results under different risk levels

DMU	$CE_j^{0.4*}$	$CE_j^{0.5*}$	$CE_j^{0.7*}$	DMU	$CE_j^{0.4*}$	$CE_j^{0.5*}$	$CE_j^{0.7*}$
C1	0.44812498	0.4481406	0.52496571	C19	0.28635642	0.27568098	0.29664794
C2	0.55467468	0.55476301	0.65019997	C20	1.65433793	1.65419769	1.8761663
C3	0.37466385	0.37439952	0.43889862	C21	1.61338154	1.67570881	1.81328431
C4	0.25690465	0.24784471	0.28932508	C22	2.64917987	2.64874801	3.0941881
C5	0.83184614	0.83155757	0.97356818	C23	0.33466401	0.3331186	0.39035625
C6	2.55753788	2.65650146	2.87454344	C24	0.50165327	0.50194024	0.58726485
C7	0.32863353	0.31622777	0.34205263	C25	0.98174997	0.98167714	1.14948119
C8	0.50115866	0.50023994	0.58719673	C26	1.39519425	1.39519999	1.63439989
C9	0.45394273	0.45343577	0.53145084	C27	0.75159364	0.75157169	0.87975906
C10	0.18708287	0.18165902	0.19493589	C28	0.2607681	0.25099801	0.27018512
C11	0.97077289	0.97108187	1.13630982	C29	0.48682646	0.46797436	0.50695167
C12	0.32726136	0.32726136	0.38374471	C30	0.53491121	0.53385391	0.62619566
C13	0.99029541	0.99102371	1.1598793	C31	0.43243497	0.41713307	0.45055521
C14	0.17029386	0.16431677	0.17606817	C32	1.24498996	1.29305839	1.39892816
C15	4.10170696	4.2605164	4.60988069	C33	0.31780497	0.30495901	0.33015148
C16	3.10737285	3.10808494	3.63790049	C34	0.73959989	0.73996486	0.86602078
C17	1.3978555	1.45189531	1.57098695	C35	1.79666357	1.86627972	2.01915824
C18	0.7132447	0.71341152	0.83454179	C36	0.39370039	0.37947332	0.4110961

Figure 3 shows the regional distribution of the institutional construction evaluation result.

Figure 3: Regional distribution of the institutional construction evaluation ranking results



Among all CMC evaluation samples, the regional distribution of the top 10 CMCs in 2020 is: 3 in East China, 3 in Southwest China, 2 in South China and 2 in Northeast China. The regional distribution of CMCs ranked 11th to 20th is: 3 in North China, 3 in Northwest China, 1 in Central China, 1 in South China, 1 in Northeast China and 1 in Southwest China. The regional distribution of CMCs beyond the top 20 is: 5 in North China, 5 in East China, 2 in Central China, 2 in Northwest China and 2 in Southwest China.

The institutional construction evaluation results show that among the 36 selected CMC samples, those with good institutional construction levels are concentrated in East China, South China, Northeast China, and Southwest China, while those with poor levels are concentrated in North China, East China, Central China, Northwest China, and Southwest China. This reflects that the overall institutional construction level of CMC samples in South China and Northeast China is relatively high, while the level in East China and Southwest China varies greatly, and the level in North China, Central China, and Northwest China is relatively low.

Table 11 presents the statistical description of the institutional construction evaluation results of the 36 CMCs by region. Among all CMCs, the highest average value is in Northeast China (0.65571767), with standard deviation 0.12712658 and average deviation 0.10399223, indicating that the institutional construction level in Northeast China is uneven but generally high. The average value in South China is 0.54453125, with standard deviation 0.05705933 and average deviation 0.04860101, indicating small differences and a relatively high overall level.

The average value in Southwest China is 0.4975011, with maximum 0.80489289 and minimum 0.2755241; the standard deviation and average deviation are the largest among all regions, indicating a large gap in institutional construction levels and reflecting unbalanced development in Southwest China.

Table 11: Statistical description of the institutional construction evaluation results

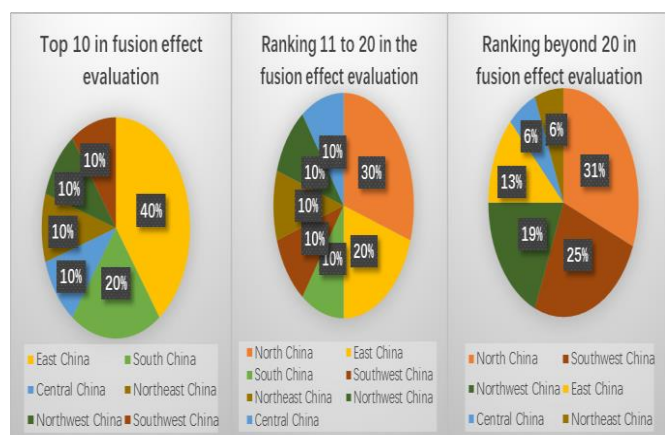
Region	Maximum	Minimum	Average	Standard deviation	Average deviation
North China	0.52506657	0.1998437	0.38824711	0.11157322	0.09659431
East China	0.74229922	0.25372367	0.47746511	0.14977282	0.13043609
Central China	0.46443156	0.41363858	0.44322132	0.02156472	0.01972183
South China	0.61094328	0.47162973	0.54453125	0.05705933	0.04860101
Northeast China	0.81170601	0.5003124	0.65571767	0.12712658	0.10399223
Northwest China	0.51039108	0.33433128	0.45030093	0.06346136	0.05217967
Southwest China	0.80489289	0.2755241	0.4975011	0.20713836	0.18209598

The average value in East China is 0.47746511, with maximum 0.74229922 and minimum 0.25372367; the standard deviation (0.14977282) and average deviation (0.13043609) indicate a large gap, though smaller than that of Southwest China. The average value in Northwest China is 0.4503093, with standard deviation 0.06346136 and average deviation 0.05217967, indicating a relatively small gap but a relatively low overall level. The average value in Central China is 0.44322132, with standard deviation 0.02156472 and average deviation 0.01972183, indicating a relatively balanced but low overall level. The average value in North China is 0.38824711, with standard deviation 0.11157322 and average deviation 0.09659431, indicating a relatively low overall level.

Analysis Of Fusion Effect Evaluation Results

Among all evaluation samples, the top three CMCs in the fusion effect evaluation results are Wulian (C15) in East China, Dongguan (C21) in South China, and Jiangjin (C35) in Southwest China. Figure 4 shows the regional distribution of the fusion effect evaluation results

Figure 4: Regional distribution of the fusion effect evaluation ranking results



Among all CMC evaluation samples, the regional distribution of the top 10 CMCs in2020 is: 4 in East China, 2 in South China, and 1 in Central China, Northeast China, Northwest China, and Southwest China, respectively. The regional distribution of CMCs ranked 11th to 20th is: 3 in North China, 2 in East China, and 1 in South China,

Southwest China, Northeast China, Northwest China, and Central China, respectively. The regional distribution of CMCs beyond the top 20 is: 5 in North China, 4 in Southwest China, 3 in Northwest China, 2 in East China, and 1 in Central China and Northeast China, respectively.

The fusion effect evaluation results show that among the 36 CMCs, more than half of the CMC samples in East China and South China perform well, ranking within the top 10, while more than half of the CMC samples in North China, Southwest China, and Northwest China perform poorly, ranking outside the 20th. This reflects that the fusion effect of CMC samples in East China and South China is generally good, while that in North China, Southwest China, and Northwest China is generally poor.

Table 12 presents the statistical description of the fusion effect evaluation results of the 36 CMCs by region. The highest average value is in South China (0.2938759), with standard deviation 0.10746454 and average deviation 0.0946549, indicating large differences but a relatively good overall fusion effect. The average value in East China is 0.20600979, with maximum 0.4177659 and minimum 0.06407485; the standard deviation (0.11940313) and average deviation (0.10594491) indicate large differences in fusion effect among CMC samples in East China. The average value in Central China is 0.18358807, with maximum 0.32099771 and minimum 0.09720279; the standard deviation (0.09822985) and average deviation (0.09160642) indicate a relatively large performance gap. The average value in Northeast China is 0.14872764, with maximum 0.21446291 and minimum 0.10710645; the standard deviation (0.04702814) and average deviation (0.03443311) indicate a relatively small gap, but the overall fusion effect is not outstanding.

The performance in Northwest China is similar to that in Northeast China, with standard deviation 0.04200356 and average deviation 0.03443311, indicating a relatively small gap but a poor overall fusion effect. The average value in Southwest China is 0.12445598, with maximum 0.3403198 and minimum 0.03872264; the standard deviation (0.10427659) and average deviation (0.08356774) indicate a poor overall fusion effect, though a few samples perform well.

Table 12: Statistical description of the fusion effect evaluation results

Region	Maximum	Minimum	Average	Standard deviation	Average deviation
North China	0.18276833	0.06072962	0.1157052	0.03788553	0.03191346
East China	0.4177659	0.06407485	0.20600979	0.11940313	0.10594491
Central China	0.32099771	0.09720279	0.18358807	0.09822985	0.09160642
South China	0.41181067	0.15189355	0.2938759	0.10746454	0.0946549
Northeast China	0.21446291	0.10710645	0.14872764	0.04702814	0.04382352
Northwest China	0.21855637	0.10470781	0.14076802	0.04200356	0.03443311
Southwest China	0.3403198	0.03872264	0.12445598	0.10427659	0.08356774

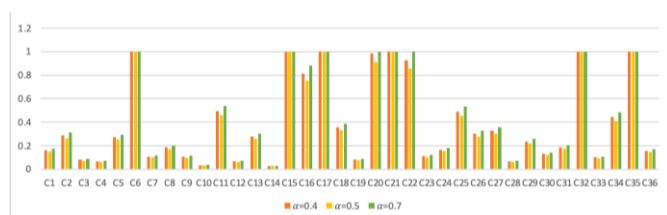
The average value in North China is 0.1157052, with maximum 0.18276833 and minimum 0.06072962; the standard deviation (0.03788553) and average deviation (0.03191346) are the smallest among all regions, reflecting a generally poor fusion effect in North China.

Analysis Of Operation Efficiency Evaluation Results

Table 13 presents the Pearson correlation test results of comprehensive efficiency under different risk levels. The comprehensive efficiency values show a strong positive correlation across different risk levels, indicating that the efficiency of each CMC maintains essentially the same relativity. This verifies the feasibility and stability of using the stochastic DEA model for operational efficiency evaluation.

Figure 5, Figure 6, and Figure 7 show the optimal efficiency, worst efficiency, and comprehensive efficiency of each CMC under different risk levels, respectively.

Figure 5. Optimal efficiency of CMCs under different risk levels

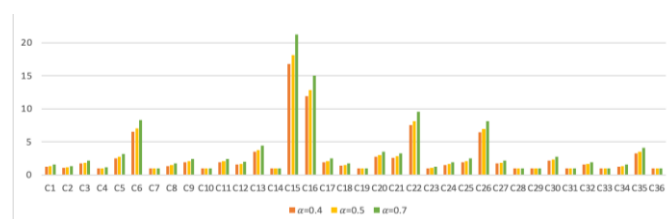


In Figure 5, the optimal efficiencies of C6, C15, C17, C21, C32, and C35 are the highest among all CMC samples. However, because efficiency measured based on the optimal frontier is obtained by comparing all DMUs with the best-performing DMU, the optimal efficiency value does not exceed 1. Therefore, the optimal efficiencies of C6, C15, C17, C21, C32, and C35 cannot be distinguished

under different risk levels, reflecting the limitation of efficiency measurement based only on the optimal frontier.

In Figure 6, the worst efficiencies of C7, C10, C14, C19, C28, C29, C31, C33, and C36 are always the lowest among all samples. However, because efficiency measured based

Figure 6: Worst efficiency of CMCs under different risk levels



on the worst frontier is obtained by comparing all DMUs with the worst-performing DMU, the worst efficiency is not less than 1. Therefore, the worst efficiencies of these CMCs cannot be distinguished under different risk levels, reflecting the limitation of efficiency measurement based only on the worst frontier.

As shown in Figure 7, the efficiency evaluation model based on double-frontier stochastic DEA overcomes this problem.

Figure 7: Comprehensive efficiency of CMCs under different risk levels

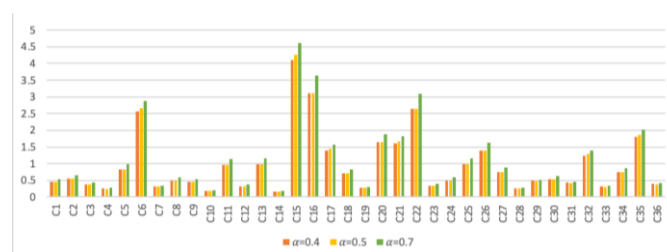


Table 13: Pearson correlation results of comprehensive efficiency under different risk levels

Pearson correlation	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.7$
$\alpha = 0.4$	1	0.99966	0.99945
$\alpha = 0.5$	0.99966	1	0.99852
$\alpha = 0.7$	0.99945	0.99852	1

Using the geometric mean method to synthesize optimal and worst efficiencies can distinguish the efficiency values of any two DMUs, and the comprehensive efficiency is more realistic and comprehensive.

CONCLUSIONS

To solve the problem that the CMC lacks scientific and effective means of achievement, inspection, and evaluation, this paper puts forward a fusion evaluation method for the evaluation of CMC based on the classical scientific evaluation method, and carries out the evaluation research on 36 CMCs based on the data-driven method. The institutional construction evaluation index system for CMC is constructed from the perspective of input, and the fusion effect evaluation index system for CMC is constructed from the perspective of output. For the two evaluation index systems, the game theory combined weighting algorithm is proposed to look for the consistency or compromise of subjective and objective weights of the indexes. In the efficiency evaluation part, based on the research on the data envelopment analysis (DEA) model and the data characteristics of the evaluation indexes of CMC, an efficiency evaluation model based on double frontier stochastic DEA is proposed. In the future, with the continuous development of CMC, a large number of time series data can be accumulated. The research on time series dynamic evaluation of CMC is also a direction worthy of in-depth exploration.

DECLARATIONS

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All data included in this study are available upon request by contact with the corresponding author.

Conflicts Of Interest:

The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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