Promotion strategies and implementation paths for green building certification system based on diffusion theory

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Abstract. Purpose: To address the lack of systematic promotion paths for green building certification systems, an analytical framework integrating social network dynamics and adaptive optimization was built to boost efficiency and cut costs. Methods: A multi-dimensional model was developed using diffusion theory, combining social network analysis, incentives, and dynamic feedback. PSO algorithm with dynamic inertia weight was adopted. Five strategies were tested with data from a Yangtze River Delta city. Results: Within 12 months, the integrated strategy had 530 certifications, 94.9% more than the traditional 272. Its unit cost was ¥33,900, 35.9% lower. Participant growth reached 84%, outperforming single strategies. Conclusion: The integrated strategy, via key node identification, graded incentives, and dynamic allocation, improved promotion effectiveness, offering a new path for the industry.

1 Introduction

Against the backdrop of the global energy crisis and climate change, the sustainable development of the construction industry, as the main area of energy consumption and carbon emissions, is crucial to achieving the "dual carbon" goal. According to statistics from the International Energy Agency (IEA) [1] energy consumption in the operation phase of buildings accounts for more than 30% of the world's total energy consumption, and carbon emissions account for 28%. Green buildings can reduce building energy consumption by 40%-60% and carbon emissions by 30%-50% through efficient energy-saving technologies, renewable energy utilization and intelligent management systems, playing a core role in energy conservation, emission reduction and ecological protection.

As a core tool for industry technical specifications and quality assurance, the green building certification system evaluates and certifies key indicators such as resource utilization efficiency and environmental impact throughout the life cycle of a building by

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establishing quantitative evaluation standards. Taking the US LEED and China GB/T 50378 certification systems as examples, their clear technical parameters and evaluation processes effectively regulate the green building market and promote the standardized application of green building technologies such as efficient insulation materials and intelligent control systems [2]. According to data from the Ministry of Housing and Urban-Rural Development, the implementation of the certification system has increased the technical compliance rate of China's green building projects from 62% in 2015 to 89% in 2023, significantly promoting the industry's technological upgrading and standardized development [2]. In the past studies, the diffusion mechanism of green architecture innovation has been studied from multiple angles. For instance, Nguyen, H. D. and Macchion, L. [4] analyzed the barriers to adoption of green building guidelines in developing countries, highlighting the role of policy incentives and cooperation between stakeholders. Teo et al. [5] identified diffusion barriers to innovative green construction products by means of a survey of SIPS builders, highlighting the need to educate the market. Xiao, Y. and Li, W. [6] investigated the stakeholder-driven diffusion of sustainable building practices, demonstrating that multi-agent cooperation accelerates technology adoption. However, there are few researches that combine social network analysis and dynamic feedback mechanism to optimize the promotion strategy of certification system, which leaves a gap in the system promotion path design.

In this paper, a quantitative analysis framework has been built for promotion strategy and implementation route of Global Center on Adaptation (GCA) based on diffusion theory. Its novelty lies in three aspects: Firstly, social network analysis, incentive mechanism design and dynamic feedback optimization are integrated into a multi-dimensional promotion strategy model. Secondly, this model is developed based on Particle Swarm Optimization (PSO) algorithm. Dynamic inertia weight adjustment is used to solve multi-objective optimization problems in promotion efficiency and cost control. Thirdly, this system is designed using multi-group control experiments to verify strategy effectiveness by integrating real data such as certification quantity, participation increase, promotion cost. These innovations fill the gap of systematic promotion path design of green building certification systems and provide a new approach to integrate social network dynamics and adaptive optimization.

2 Design of green building certification system promotion strategy based on diffusion theory

2.1 Differentiated promotion strategy combined with incentive mechanism

The promotion of green building certification involves multiple parties, whose interests and motivations vary significantly. For developers, tax incentives and policy support are designed; for owners, subsidies and low-interest loans are implemented; for construction units, technical training is provided and a qualification reward mechanism is established to stimulate the enthusiasm of all parties to participate [7].

2.2 Adaptive promotion strategy based on dynamic feedback

Build a dynamic feedback system for green building certification promotion, collect data such as certification quantity, market demand, policy and technological innovation in real time through multi-source modules. Use big data analysis technology to clean and integrate data and establish an evaluation model. When the system analysis finds problems or policy changes, it automatically triggers strategy adjustments to achieve dynamic feedback and adaptive optimization, and improve promotion efficiency [8].

3 Algorithm design and optimization

3.1 Key influence node identification strategy based on social network analysis

The particle swarm optimization (PSO) algorithm was chosen for its efficiency in multi-objective optimization, as validated in previous studies on technology diffusion path planning [8]. Compared to recent optimizers (e.g., COVID-19 optimizer, Harris hawks optimizer), PSO offers unique advantages: 1) It requires fewer parameters and simpler implementation, making it suitable for dynamic adjustment in real-time promotion scenarios; 2) Its social learning mechanism aligns with the stakeholder collaboration model of green building certification systems; 3) Previous research has shown PSO outperforms genetic algorithms in convergence speed for similar resource allocation problems [9]. The algorithm parameters were initialized based on the adaptive inertia weight strategy proposed by Yang et al (2018), which balances global and local search capabilities.

Assume that the particle swarm contains N particles, and the position vector $Xi = (xi1, xi2, \cdots, xiD)$ of each particle i represents a promotion path plan, where D is the dimension of the path decision variable. For example, $xi1$ can represent the proportion of capital investment in online promotion, and $xi2$ represents the frequency of offline activities. The velocity vector $Vi = (vi1, vi2, \cdots, viD)$ controls the movement of particles in the solution space and determines the adjustment direction and amplitude of the promotion path plan. In actual promotion, cost and coverage are two key considerations. To balance the relationship between the two, a dual-objective optimization function is constructed:

$$F(Xi) = \omega 1 C(Xi) \max(C) + \omega 2(1 - R(Xi) \max(R)) \tag{1}$$

$\omega 1$ and $\omega 2$ are weight coefficients, and $\omega 1 + \omega 2 = 1$. $C(X_i)$ denotes the total promotion cost under the strategy defined by Xi, calculated as $C(Xi) = \sum\ j = 1M(cj \times xij)$, where cj is the unit cost of the j-th promotion channel. $R(X_i)$ represents the certification coverage, defined as the ratio of certified projects to total potential projects, computed via $R(Xi) = P(Xi)/P0$, where $P(Xi)$ is the predicted number of certifications and $P0$ is the regional project pool size. $\max(C)$ and $\max(R)$ are the theoretical maximum values of promotion cost and certification coverage, respectively, used for normalization.

The particle update rule is the core of the PSO algorithm, which is implemented by the following formula:

$$\begin{aligned} v_{ij}(t+1) &= \omega v_{ij}(t) + c_1 r_{1j}(t)\left(p_{ij} - x_{ij}(t)\right) + c_2 r_{2j}(t)\left(g_j - x_{ij}(t)\right) \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1) \end{aligned} \tag{2}$$

ω is the inertia weight, which adjusts the degree of inheritance of the particle's previous velocity. A larger ω helps the particle to conduct a global search in the solution space and explore a wider area; a smaller ω makes the particle focus more on local search and fine-tune the current solution. c_1 and c_2 are learning factors, which control the degree to which the particle learns from the individual optimal position p_{ij} and the global optimal positiong_j respectively. r_{1j} and r_{2j} are random numbers in the interval [0,1]. The introduction of randomness can prevent the algorithm from falling into the local optimum too early. t represents the number of iterations. As the iteration proceeds, the particle continuously adjusts its position and gradually approaches the optimal promotion path plan.

3.2 Certification system diffusion prediction algorithm considering the influence of multiple factors

The diffusion of the green building certification system is not the result of a single factor, but is affected by a combination of policies and regulations, economic environment, technical level, public perception and other factors. Suppose the influencing factor set is $\mathbf{F} = \{F_1, F_2, \cdots, F_M\}$, where F_m ($m = 1,2, \cdots, M$) represents the m influencing factor. Taking policies and regulations as an example, the intensity of the green building subsidy policy issued by the government (F_1) directly affects the enthusiasm of enterprises and owners to participate in certification; the GDP growth rate of the construction industry (F_2) reflects the economic development of the industry, which in turn affects the investment scale and certification needs of green building projects; the research and development and application of new technologies (such as the emergence of high-efficiency energy-saving materials) will change the technical level of green buildings (F_3) and promote the diffusion of the certification system.

When constructing a certification diffusion model with multiple factors, the nonlinear regression equation is used:

$$y = f(\mathbf{F}) + \epsilon \tag{3}$$

Among them, y is the diffusion index of the certification system, such as the number of new certification projects per unit time; $f(\mathbf{F})$ is a nonlinear mapping function. Since there is often a complex nonlinear relationship between various influencing factors and certification diffusion, a nonlinear function is needed to accurately characterize it; ϵ is a random error term, which is used to represent the impact of other random factors not considered by the model on the diffusion index.

In order to improve the prediction accuracy, a deep neural network (DNN) is introduced to construct a diffusion prediction algorithm. DNN has a strong nonlinear fitting ability and can automatically learn the complex relationship between various influencing factors and certification diffusion indicators. Assume that the number of neurons in the input layer is M, corresponding to M influencing factors; there are L hidden layers, and the number of neurons in the l layer is n_l; the number of neurons in the output layer is 1, which is used to output the predicted certification system diffusion index. The output h_l of the l layer of neurons in the network is calculated by the following formula:

$$h_l = \sigma(\mathbf{W}_l h_{l-1} + \mathbf{b}_l) \tag{4}$$

Among them, $\mathbf{W}_l$ is the weight matrix from the $l - 1$ layer to the l layer, which determines the influence of the output of the neurons in the previous layer on the neurons in the current layer; $\mathbf{b}_l$ is the bias vector, which is used to adjust the activation threshold of the neurons; $\sigma(\mathbf{W}_l h_{l-1} + \mathbf{b}_l)$ is the activation function, such as the ReLU function, which introduces nonlinear factors into the network so that the network can learn more complex patterns.

The network is trained with historical data. The training data uses the green building certification data of a certain region in the past five years, specifically covering policies and regulations (such as the intensity of government green building subsidy policies, the degree of perfection of regulations and other quantitative indicators), economic environment (GDP growth rate of the construction industry, fixed asset investment scale, etc.), technical level (R&D investment and application of new technologies such as high-efficiency energy-saving materials and intelligent control systems), social cognition (public awareness and acceptance indicators of green buildings obtained through questionnaires) and certification results (the number of newly certified projects in each year, the distribution of certification levels, etc.).

After data cleaning (processing outliers and missing values) and standardization, all data are divided into training set and test set at a ratio of 8:2, where the training set is used for model parameter learning and the test set is used to evaluate the model prediction performance. The mean square error (MSE) is used as the loss function:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{5}$$

Among them, N is the number of training samples, y_i is the actual diffusion index value, and $\hat{y}_i$ is the model prediction value. The network parameters are updated using the stochastic gradient descent (SGD) algorithm. By continuously adjusting the weight matrix $\mathbf{W}_l$ and the bias vector $\mathbf{b}_l$, the loss function is gradually reduced, thereby achieving an accurate prediction of the diffusion trend of the certification system [10]. For example, in the actual application of a certain region, the algorithm is used to predict the number of green building certification projects in the next year, which provides an important reference for the local formulation of promotion policies and resource allocation.

3.3 Algorithm performance optimization and improvement plan

3.3.1 Particle swarm optimization algorithm performance optimization

Although the particle swarm optimization algorithm has certain advantages in solving optimization problems, it is easy to fall into the local optimum in the later stage of iteration, resulting in the inability to find the global optimal solution. To solve this problem, a strategy for dynamically adjusting the inertia weight ω is proposed:

$$\omega = \omega\mathrm{min} + (\omega\mathrm{max} - \omega\mathrm{min})(1 - tT\mathrm{max})\alpha \tag{6}$$

Among them, ω min and ω max are the minimum and maximum values of the inertia weight, Tmax is the maximum number of iterations, and α is the adjustment coefficient. In the early stage of the algorithm, t is small and ω is close to ω max. At this time, the particles have a large speed and can conduct extensive searches in the solution space and explore more potential solutions; as the iteration proceeds, t gradually increases, ω gradually decreases, the particle speed decreases, and it begins to focus on the local search in the current area and fine-tune the better solutions that have been found [11]. Through this dynamic adjustment strategy, the global search and local search capabilities of the algorithm are effectively balanced [12].

3.3.2 Diffusion prediction algorithm performance optimization

For the diffusion prediction algorithm, in order to reduce model complexity and improve operating efficiency, a feature selection method based on mutual information is adopted. Mutual information can measure the degree of dependence between two random variables, by calculating the mutual information $MI(F_m, y)$ between each influencing factor F_m and the certification diffusion index y:

$$MI(F_m, y) = \sum_{x\in X} \sum_{y\in Y} p(x, y)\log\frac{p(x,y)}{p(x)p(y)} \tag{7}$$

$p(x, y)$ is the joint probability distribution of F_m and y, and $p(x)$ and $p(y)$ are marginal probability distributions. The higher the mutual information value, the stronger the correlation between the influencing factor and the certification diffusion index. The top K influencing factors with higher mutual information values (K is a threshold determined based on the balance between model complexity and prediction accuracy, such as K=5 or K=8). The algorithm flow chart is shown in Figure 1.

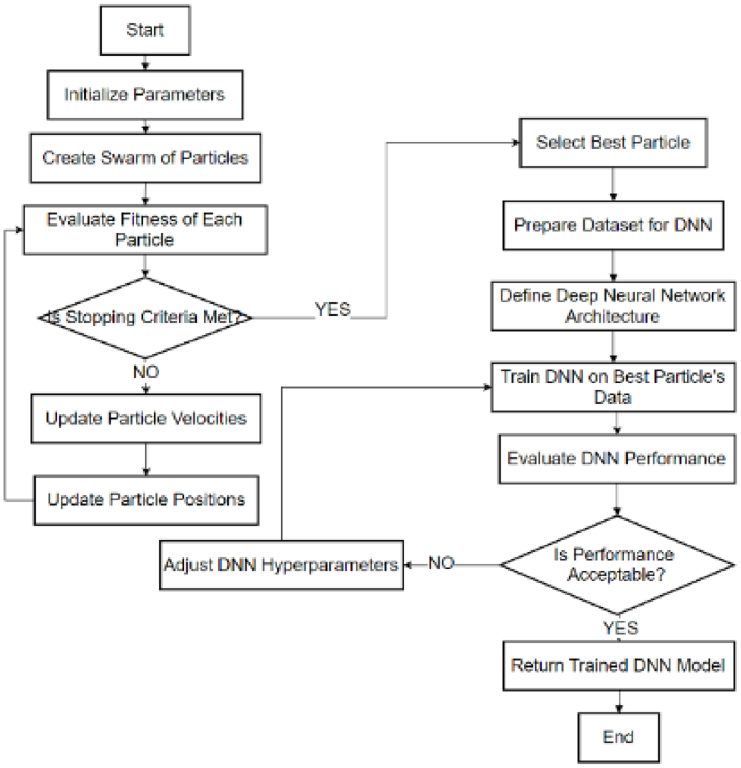


Fig. 1. Algorithm flow chart.

In addition, in order to solve the gradient vanishing problem that may occur when the number of layers of deep neural networks increases, the network structure is optimized and the residual connection technology is adopted. The residual connection allows the network to directly learn the residual between the input and output instead of directly learning the complex mapping relationship, so that the gradient can be back-propagated more smoothly, thereby improving the training efficiency and prediction accuracy of the network [13]. Through these optimization schemes, the performance of the diffusion prediction algorithm is effectively improved, enabling it to more accurately and efficiently predict the diffusion trend of the green building certification system, and provide reliable support for the formulation and adjustment of promotion strategies [14].

4 Experimental simulation design and analysis

4.1 Experimental scenario and parameter setting

An economically developed city in the Yangtze River Delta is selected as the experimental scenario. The construction industry in the region is active and the foundation for the development of green buildings is good. However, the promotion of the certification system has regional imbalances and large differences in the enthusiasm of the participating entities, which has typical research value. Data on construction projects, GDP growth rate, fiscal subsidy policies, public environmental awareness, and other data in the region in the past five years are collected to build an experimental basic database.

4.2 Comparison of simulation experiments under different promotion strategies

This simulation was implemented using Python 3.8, using the NetworkX library for social network analysis, and using the TensorFlow framework to build a deep neural network model. The input data included five years of construction project history, GDP growth rate, fiscal subsidy policy, and public environmental awareness in the Yangtze River Delta region, and Pandas was used for data cleaning and normalization preprocessing. Specifically, the data preprocessing process included: identifying and processing missing values in construction project data through interpolation methods based on adjacent years; detecting and correcting outliers in GDP growth rate data through the interquartile range (IQR) method; using the Min-Max scaling method to standardize fiscal subsidy policy intensity data to the range of [0,1]; and performing one-hot encoding on categorical variables in the public environmental awareness survey data. The output metrics included certification quantity, participation growth rate, and promotion cost, validated against real-world project data from the local construction bureau. Design 5 groups of comparative experiments:

Table 1. Changes in the number of green building certifications under different promotion strategies.

Experimental period (month)	Traditional promotion (n)	Social network analysis (n)	Incentive mechanism (n)	Dynamic feedback (n)	Comprehensive strategy (n)
1	85	92	98	95	103
2	102	115	122	118	130
3	120	140	155	148	170
4	138	168	188	176	210
5	155	195	215	205	250
6	172	222	242	232	290
7	188	248	268	258	330
8	205	275	295	285	370
9	222	302	322	312	410
10	238	328	348	338	450
11	255	355	375	365	490
12	272	382	402	392	530

Traditional promotion strategy: Relying solely on policy propaganda (e.g., government website announcements) and market natural drive, with no targeted incentives. The cost model assumes uniform distribution of resources across channels, calculated as C=1.2×t (million RMB), where t is the number of months.

Promotion strategy based on social network analysis: Identifies key nodes (degree centrality > 0.3 and betweenness centrality > 0.2) such as top 5 developers and municipal construction bureaus. The strategy allocates 60% of resources to key nodes for demonstration projects, with cost function $C = (0.8 \times t) + 0.2 \times \sum_{k=1}^{K} w_k$. where w_k is the weight of key node k [15].

Promotion strategy combined with incentive mechanism: Implements tiered incentives:

Developers: 15% tax reduction for certified projects (cost modeled as $C1$=0.05×t×N, N=number of certified projects)

Owners: 500 RMB/m² subsidy ($C2$=0.1×t×S, S=certified area in m²)

Construction units: Technical training grants ($C3=0.03\times t\times M$, M=number of trainees)

Total cost: $C=C1+C2+C3$

Adaptive promotion strategy based on dynamic feedback: Uses a sliding window (window size=3 months) to adjust resource allocation. When online promotion ROI < 1.2, 20% of offline resources are reallocated. The cost function dynamically updates as $C=\lambda(t)\times C0$, where $\lambda(t)$ is the adaptive coefficient [16].

Comprehensive promotion strategy: Integrates the above mechanisms: 40% resources for key nodes, 30% for incentives, and 30% for dynamic reallocation. The cost model is $C=(0.4\times C2)+\{0.3\times(C1+C2+C3)\}+(0.3\times\lambda(t)\times C0)$.

The simulation model was run to record the number of green building certifications, growth rate of participating entities, promotion costs and other data under each strategy within 12 months. The results are summarized in Table 1 and Table 2.

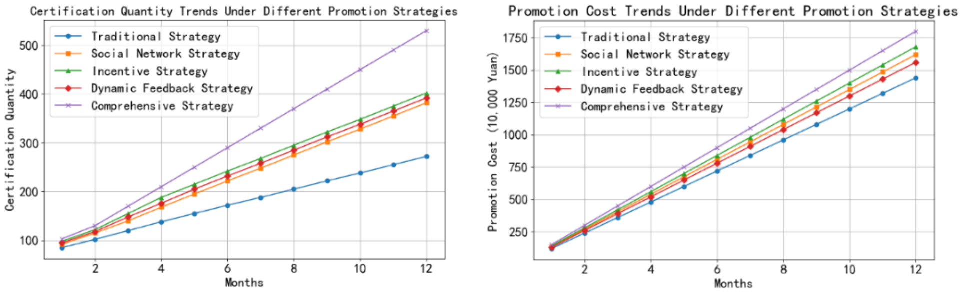
Table 2. Changes in promotion costs and growth rates of participating entities under different promotion strategies (10,000 RMB).

Experimental period (month)	Traditional promotion	Social network analysis	Incentive mechanism	Dynamic feedback	Comprehensive strategy
1	1.20	0.00	0.14	0.13	0.15
2	0.24	0.27	0.28	0.26	0.30
3	0.36	0.41	0.42	0.39	0.45
4	0.48	0.54	0.56	0.52	0.60
5	0.60	0.68	0.70	0.65	0.75
6	0.72	0.81	0.84	0.78	0.90
7	0.84	0.95	0.98	0.91	1.05
8	0.96	1.08	1.12	1.04	1.20
9	1.08	1.22	1.26	1.17	1.35
10	1.20	1.35	1.40	1.30	1.50
11	1.32	1.49	1.54	1.43	1.65
12	1.44	1.62	1.68	1.56	1.80

4.3 Precise quantitative analysis and result interpretation based on simulation data

4.3.1 Comparative analysis of the number of certifications and promotion costs

It can be clearly seen from Figure 2 (a) that the number of certifications under each strategy has increased over time, but the growth rate is significantly different. The 94.9% increase in the comprehensive strategy's certification quantity (530 vs. 272) stems from its multi-faceted approach: social network analysis identifies key propagators (e.g., government departments with high betweenness centrality), incentive mechanisms reduce adoption barriers for developers (tax incentives), and dynamic feedback reallocates resources to underperforming channels. By contrast, the traditional strategy lacks targeted optimization, leading to slower growth [17]. The cumulative number of certifications for the traditional promotion strategy in 12 months, is 272, while the comprehensive promotion strategy has reached 530, an increase of 94.9% over the traditional strategy. The number of certifications for the single strategies based on social network analysis, incentive mechanism, and dynamic feedback are 382, 402, and 392, respectively, indicating that the three single strategies can improve the promotion effect, but the comprehensive strategy has achieved a greater growth through complementary advantages, verifying the effectiveness of strategy fusion. From the simulation data, we can see that the number of certifications for the comprehensive strategy increased by 94.9% (530 vs. 272). This is due to its integration of social network analysis to lock in key communication nodes (such as government departments with high intermediary centrality to accelerate information diffusion), incentive mechanisms to reduce developer certification costs (tax incentives, etc. to eliminate financial concerns), and dynamic feedback to optimize resource allocation (real-time adjustment of investment based on channel effects). These three mechanisms break down communication barriers in multiple dimensions. Traditional strategies lack targeted optimization, and single strategies only solve specific bottlenecks and cannot work together and complement each other. Therefore, the comprehensive strategy achieves a significant increase in the number of certifications through the integration of advantages.



(a) **(b)**

Fig. 2. Comparative analysis of the number of certifications and promotion costs (a) Trends in the number of certifications under different promotion strategies, (b) Trend of promotion cost changes under different promotion strategies.

As shown in Figure 2(b), the cost of the traditional promotion strategy increases linearly over time, with a total cost of 14.4 million Chinese Yuan (CNY) in 12 months. Although the comprehensive promotion strategy has a higher initial cost (1.5 million yuan), the cost growth slows down in the later period through dynamic feedback optimization of resource allocation, and the final total cost is 18 million yuan, with a unit certification cost of only 33,900 yuan, lower than the 52,900 yuan of the traditional strategy. The incentive mechanism strategy has the highest cost (16.8 million yuan) due to continuous subsidies, indicating that a single incentive measure needs to be combined with other strategies to maximize cost-effectiveness. The unit certification cost of the comprehensive strategy (33,900 CNY) is 35.9% lower than the traditional strategy (52,900 CNY) because dynamic feedback optimizes resource allocation—for example, reducing offline event frequency when online promotion proves more cost-effective. In contrast, the incentive mechanism strategy's high cost (16.8 million CNY) reflects unadjusted subsidies, highlighting the need for feedback-driven optimization.

4.3.2 Comparative analysis of growth rates of participating entities

As shown in Figure 3, the comprehensive promotion strategy has the best effect in improving the enthusiasm of participating entities, with a growth rate of 84% in 12 months, significantly higher than the 36% of the traditional strategy. The strategy based on social network analysis drives through key nodes, with a growth rate of 60%; the incentive mechanism strategy directly stimulates the participation of entities, with a growth rate of 72%; the dynamic feedback strategy adjusts the strategy according to the market, with a growth rate of 60%. Each single strategy plays its advantages at different stages, and the comprehensive strategy integrates them to form a continuous growth momentum.

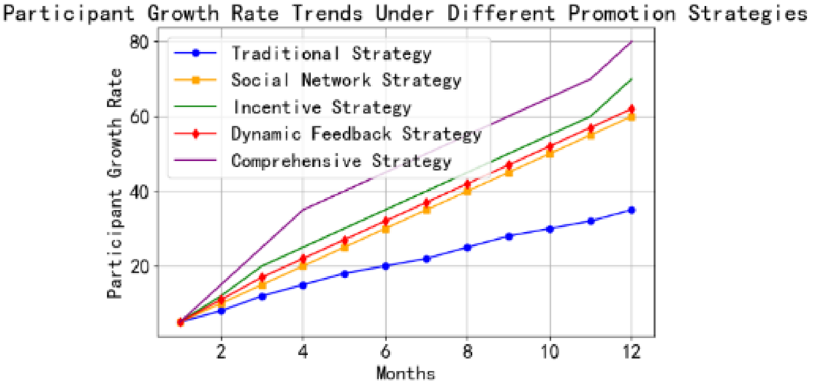


Fig. 3. Trend of growth rate of participating entities under different promotion strategies.

5 Conclusion

This study constructs a quantitative analysis framework for the promotion strategy of the green building certification system (GCA) based on the diffusion theory. By integrating social network analysis, incentive mechanism design and dynamic feedback optimization, a multi-dimensional promotion strategy model is formed, and the particle swarm optimization (PSO) algorithm is used to achieve multi-objective optimization of promotion efficiency and cost control. The simulation experiment takes a developed city in the Yangtze River Delta as the scenario to compare the promotion effects of traditional strategies, strategies based on social network analysis, incentive mechanism strategies, dynamic feedback strategies and comprehensive strategies. The data show that the number of certifications of the comprehensive strategy reached 530 within 12 months, an increase of 94.9% compared with the 272 traditional strategies, and the unit certification cost was only 33,900 yuan, a decrease of 35.9% compared with the 52,900 yuan of the traditional strategy, and the growth rate of participating entities reached 84%. Among the single strategies, the number of certifications of the incentive mechanism strategy was 402 but the cost was 16.8 million yuan, the number of certifications of the social network analysis strategy and the dynamic feedback strategy were 382 and 392 respectively, and the cost control was better than the incentive mechanism strategy. The research shows that the comprehensive strategy achieves complementary advantages through key node identification, hierarchical incentives and dynamic resource allocation, significantly improves the promotion efficiency, fills the gap in the design of systematic promotion paths for the green building certification system, and provides a new path for integrating social network dynamics and adaptive optimization. In the future, the application scenarios can be expanded to different regions, the simulation cycle can be extended to analyze the long-term effects, emerging technologies such as blockchain can be integrated, policy coordination with the carbon trading market can be studied, and a fine-grained stakeholder behavior model can be constructed.

References

1. Y. Liu, “Research on innovation in construction project management and green construction management,” Constr. Eng. Manag,vol. 7, pp. 79–81, April 2025.
2. A. Chen, C. Wencong, and X. Xiaohui, “Theoretical analysis and practical approach to the construction of China's national trail system: an empirical study based on the Zhejiang Ring Trail,” Sports Sci,vol. 44, pp. 45–57, December 2024.

3. H. D. Nguyen and L. Macchion, “A comprehensive risk assessment model based on a fuzzy synthetic evaluation approach for green building projects: the case of Vietnam,” Eng. Constr. Archit. Manag,vol. 30, pp. 2837–2861, July 2023.
4. R. Teo, R. Grosser, H. Thuppal, and M. B. Statter, “‘Sip & Share’: Building resilience in surgery residency through moral distress rounds,” J. Surg. Educ,vol. 80, pp. 556–562, July 2023.
5. Y. Xiao and W. Li, “Stakeholder-driven sustainable technology application in fashion manufacturing enterprises and performance impact,” Pol. J. Environ. Stud,vol. 34, pp. 1389–1402, February 2025.
6. Z. Wang, Z. Wei, and J. Cheng, “New quality productivity empowers the realization of agricultural ecological product value: theoretical logic and implementation path,” Chin. J. Eco-Agric,vol. 32, pp. 1756–1765, October 2024.
7. S. Mollaoglu, C. Chergia, E. Ergen, and M. Syal, “Diffusion of green building guidelines as innovation in developing countries,” Constr. Innov,vol. 16, pp. 11–29, January 2016.
8. A. P. McCoy, Y. H. Ahn, and A. R. Pearce, “Towards establishing diffusion barriers for innovative green building products: A survey of SIPS builders,” J. Green Build,vol. 7, pp. 153–176, April 2012.
9. E. Yang, Y. Hua, and T. Diciccio, “Diffusion of innovation in sustainable building practices and the role of stakeholders,” J. Green Build,vol. 13, pp. 91–102, October 2018.
10. S. Verma, S. N. Mandal, S. Robinson, and D. Bajaj, “Diffusion patterns and drivers of higher-rated green buildings in the Mumbai region, India: A developing economy perspective,” Intell. Build. Int,vol. 14, pp. 393–413, October 2022.
11. L. Gao, Y. Ren, T. Wang, and W. Song, “Research on the creation path of regional forest food brands under the background of rural revitalization: Grounded analysis based on the perspective of multi-agent collaboration,” J. Beijing For. Univ. (Soc. Sci. Ed.),vol. 20, pp. 65–72, September 2021.
12. X. Xu and P. Wu, “The evolution of green agricultural development mechanism,” J. China Agric. Univ,vol. 27, pp. 259–273, January 2022.
13. C. Wang and F. Liu, “Research on the path to improve the willingness of Weinan shadow puppet consumption through ‘Internet+’,” Finance Manag. Int. Acad. Forum, vol. 3, pp. 54–57, May 2024.
14. Z. Zhong and Z. Gou, “Adopting cross-laminated timber in architectural design to reduce embodied carbon emission in China based on the diffusion of innovation theory,” Build. Res. Inf,vol. 51, pp. 834–852, July 2023.
15. F. Halila, J. Tell, M. Hoveskog, and Q. Lu, “The diffusion of green innovation technology in the construction industry: European passive house knowledge transfer to China,” Prog. Ind. Ecol. Int. J,vol. 11, pp. 164–181, June 2017.
16. N. Li, “Evaluation of ecological product value in Qinling Mountains based on AHP-fuzzy comprehensive evaluation method: A case study of Shangluo City,” Agric. Eng,vol. 14, pp. 160–166, August 2024.
17. K. Chen, “Analysis of factors affecting the application and optimization of air pollution control technology in environmental protection engineering,” Nat. Sci. Res,vol. 2, pp. 45–47, January 2025.