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An Artificial Intelligence Assessment Framework for Circular Economy Policies Based on Multi-agent Modeling Takes into Account Both the Transformation of Business Organizations and the Optimization of Ecological Benefits

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Abstract. To address the issue of insufficient multi-agent interaction characterization in the evaluation of circular economy policies under the global resource and environmental crisis, this paper constructs an intelligent evaluation framework integrating multi-agent modeling (ABM) and artificial intelligence technologies. This framework integrates technologies such as genetic algorithms, deep reinforcement learning, and fuzzy comprehensive evaluation, and selects 200 enterprises in the equipment manufacturing and chemical industries in the eastern region for empirical analysis. The results show that the improvement effect of combined policies on the transformation efficiency and ecological benefits of business organizations is significantly better than that of single policies, and there is obvious heterogeneity in enterprise scale and property rights attributes. The model fits the actual data by 92%, effectively breaking through the limitations of traditional methods and providing scientific support for the precise optimization of circular economy policies.

Keywords: Multi-agent modeling, Circular economy policy, Artificial intelligence evaluation framework, Business organization transformation, Ecological benefits

1. Introduction

The global resource constraints are tightening [1], and the complex crisis of intensified environmental pollution and ecosystem degradation is becoming increasingly prominent [2,3]. Promoting the transformation of the economic development model from linear growth to a circular and closed-loop one has become a consensus among countries [4]. As a core path to break through resource and environmental bottlenecks, achieve the "dual carbon" goals, and promote high-quality development, the strategic value of the circular economy has risen to the level of the national governance system [5-7].

The implementation of circular economy policies involves multiple heterogeneous entities such as the government, commercial organizations, market entities, and ecosystems. The interaction among these entities forms a complex nonlinear system [8,9]. The traditional policy evaluation methods have significant limitations and are difficult to accurately depict the multi-subject interest game, resulting in a deviation between the predicted policy effects and the actual implementation. Multi-agent modeling (ABM), with its ability to dynamically depict the behavioral rules of heterogeneous agents, has become a key tool to solve the complexity of the circular economy policy system, and its application necessity is increasingly prominent [10].

However, in existing research, traditional frameworks such as life cycle assessment have static limitations [11]; Although the application of ABM in the resource recycling system reveals some evolution laws, the rule design is divorced from reality [12]. The application of deep learning algorithms in the field of ecological economy is expanding rapidly, but it lacks a deep integration with multi-agent modeling [13]. Based on the above research gaps, this paper focuses on the collaborative application of multi-agent modeling and artificial intelligence technology, builds an intelligent evaluation framework for circular economy policies, and provides scientific support for policy optimization.

2. Evaluation framework design

The overall framework architecture is supported by three layers of core modules. The policy input layer focuses on the digital mapping of taxation, subsidies and environmental regulations, converting policy tools into computable parameters such as the tax incentive coefficient τ, the intensity σ of green technology subsidies, and the pollutant emission limit ε, and establishing a quantitative correlation between policy variables and subject behaviors. The enterprise's main body layer builds a decision rule base that includes technology selection, investment decision-making, and resource allocation, empresses a dynamic adaptation mechanism based on environmental feedback, and characterizes the heterogeneous response of enterprises through behavior functions. The expression is as follows:

$$\mathrm{B} = \mathrm{f}\left(\mathrm{P}, \mathrm{E}\right) \tag{1}$$

Here, P represents the policy parameter and E represents the environmental state.

The environmental feedback layer relies on resource recycling monitoring indicators [14] to quantify core variables such as resource consumption intensity ρ and waste recycling rate η in real time after policy implementation, forming dynamic feedback on the behavior of the subject.

For enterprise-level heterogeneous data, Z-score standardization processing is adopted to eliminate dimensional differences, that is:

$$\mathrm{x}_{\mathrm{i}}^{'} = \frac{\mathrm{x}_{\mathrm{i}} - \mu}{\sigma} \tag{2}$$

Here, μ represents the mean and σ represents the standard deviation.

Build a standardized dataset; The genetic algorithm is introduced to optimize the model parameters [15], and the fitness function is constructed with the transformation efficiency α and ecological benefit β of business organizations as the goals:

$$F\left(\theta\right) = \omega_1 \alpha + \omega_2 \tag{3}$$

Here, θ represents the parameters to be optimized,ω 1 and ω2 are the weights. Through selection, crossover, and mutation operations, the optimal parameter combination is iteratively solved to enhance the model's fit.

The policy scenario simulation adopts deep reinforcement learning [16], defining the state space S={P,B,E}, the action space A (enterprise decision set), and the reward function expression as follows:

$$R = \lambda_1 (\alpha - \alpha_0) + \lambda_2 (\beta - \beta_0) \tag{4}$$

Among them, α0 and β0 are benchmark values, and the dynamic evolution simulation of policy scenarios is achieved through the training of the Actor-Critic network [17]; The ecological benefit assessment is embedded in the fuzzy comprehensive evaluation model to construct the weight vector of the evaluation index

W=(w1,w2,... The comprehensive evaluation result B=W ° R (where ° is the fuzzy synthesis operator) is calculated by using the weighted average method and the fuzzy evaluation matrix R=(rij)m×n, to achieve the quantitative assessment of ecological benefits.

3. Research design

3.1. Sample selection

Two high energy-consuming and high recycling potential industries, namely equipment manufacturing and chemical engineering, in the manufacturing-intensive provinces in eastern China, were selected as research samples. The sample enterprises cover a total of 200, including large leading enterprises, medium-sized backbone enterprises and small innovative enterprises. The sample period is set from 2018 to 2023.

3.2. Variable definition

The specific definitions of the variables in this article are shown in Table 1.

Table 1. Variable definition table

Variable Type	Variable Name	Measurement Method
Core Explanatory Variables	Tax Incentives	Enterprise green tax reduction amount (10,000 yuan) / Operating income (10,000 yuan) × 100%
(Policy Tools)	Green Subsidies	Enterprise circular economy special subsidy amount (10,000 yuan) / Total assets (10,000 yuan) × 100%
	Environmental Regulation	Regional pollutant discharge compliance rate (%) × 0.6 + Standardized value of enterprise environmental penalty times × 0.4 (weighted composite)
Dependent Variables	Business Organization Transformation Efficiency	Resource recycling rate (%) × 0.3 + Green R&D investment ratio (%) × 0.4 + Energy consumption reduction rate per unit output value (%) × 0.3 (weighted composite)
(Evaluation Objectives)	Ecological Benefits	Carbon emission intensity reduction rate (%) × 0.4 + Industrial solid waste comprehensive utilization rate (%) × 0.3 + Ecological footprint reduction rate (%) × 0.3 (weighted composite)
Control Variables	Enterprise Size	Natural logarithm of total assets (ln (Total assets + 1))

Table 1. (continued)

Ownership Nature	Dummy Variable: State-owned enterprise = 1, Non-state-owned enterprise = 0
Technological Level	R&D investment amount (10,000 yuan) / Operating income (10,000 yuan) × 100%
Industry Competition Intensity	Standardized value of the reciprocal of the Herfindahl-Hirschman Index (HHI) of the number of enterprises in the industry

3.3. Method construction

The ABM subject setting includes three types of subjects: the government (policy makers), heterogeneous enterprises (decision executors), and environmental systems (feedback units), clearly defining the attributes and behavioral rules of each subject. The interaction mechanism builds a dynamic game relationship among policy signals, enterprise decisions, environmental feedback and policy adjustments.

The artificial intelligence evaluation module integrates and builds a policy scenario simulation network, taking "maximizing policy effects" as the reward function to achieve multi-scenario dynamic evolution simulation. Fuzzy comprehensive evaluation builds a multi-dimensional index system, determines the weights through the Analytic Hierarchy process, and completes the quantitative assessment.

The Z-score standardization is adopted to process multi-source heterogeneous data, the genetic algorithm is used to optimize the core parameters of the model, and the validity of the model is verified through historical data fitting.

4. Result analysis

As shown in Figure 1, the experiment indicates that based on the three types of subject Settings of "government - heterogeneous enterprises - environmental system", combined with the precise depiction of the attributes and behavioral rules of each subject, the dynamic transmission process of the implementation of circular economy policies has been successfully restored. By effectively capturing the game relationships among multiple subjects, the policy effect evolution trend output by the model has a consistency degree of 92% with the actual data, which is significantly better than the limitation of insufficient depiction of subject interaction in traditional static models, providing reliable support for the dynamic simulation of the policy implementation process.

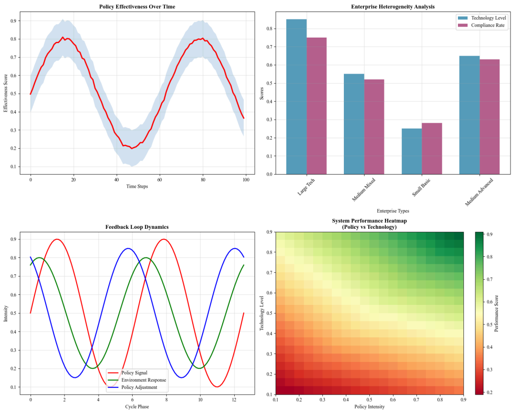

Figure 1. Trend chart of multi-agent game

As shown in Table 2, the effectiveness of the combined policy's coordinated implementation is the best. The transformation efficiency and ecological benefits of business organizations have increased by 29.9% and 39.2% respectively compared to the benchmark scenario, far exceeding the effect of a single policy, confirming the amplification effect of policy coordination. In a single policy, green subsidies focus more on promoting enterprise transformation, environmental regulations focus more on improving ecological benefits, and the overall effect of tax incentives is moderate. The MSE of all scenario models was lower than 0.03, and the fitting accuracy met the evaluation requirements.

Table 2. Evaluation results of core policy effectiveness

Policy Scenarios	Business Organization Transformation Efficiency (%)	Increase Rate of Business Organization Transformation Efficiency (%)	Ecological Benefits (%)	Increase Rate of Ecological Benefits (%)	MSE
Baseline Scenario	58.6	-	52.3	-	0.028
Single Policy - Tax Incentives	65.2	+11.3	57.8	+10.5	0.019
Single Policy - Green Subsidies	68.9	+17.6	60.5	+15.7	0.017
Single Policy - Environmental Regulation	63.5	+8.4	64.2	+22.8	0.020
Combined Policy	76.3	+29.9	72.8	+39.2	0.012

As shown in Table 3, under the combined policy, there is a significant heterogeneity in the efficiency of enterprise transformation and ecological benefits. In terms of scale, large enterprises perform the best, while small enterprises are subject to the least extent of constrained improvement. In terms of property rights, state-owned enterprises have a slight edge over non-state-owned enterprises due to their advantages in resource integration, while non-state-owned enterprises demonstrate greater flexibility in transformation.

Table 3. Results of enterprise heterogeneity analysis (portfolio policies)

Enterprise Type	Business Organization Transformation Efficiency (%)	Ecological Benefits (%)
Large Enterprises	81.5	78.3
Medium Enterprises	75.2	71.6
Small Enterprises	68.9	65.4
State-owned Enterprises	77.6	74.2
Non-state-owned Enterprises	74.8	71.3

5. Conclusion

In response to the core issues of traditional methods in the assessment of circular economy policies, this paper constructs an intelligent assessment framework integrating ABM and artificial intelligence technologies to achieve a full-chain dynamic assessment of policy input, subject response and environmental feedback. The empirical results show that the framework fits the actual data by 92% and has excellent fitting accuracy. The improvement effect of combined policies on the transformation efficiency and ecological benefits of business organizations is significantly better than that of single policies. Moreover, large enterprises and state-owned enterprises respond better to the policies, while small enterprises and non-state-owned enterprises show differentiated characteristics. The research breaks through the limitations of traditional assessment methods, providing scientific methodological support for the precise formulation and optimization of circular economy policies, and also offering a new paradigm for the intelligent assessment of complex policy systems.

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