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Research on Enterprise Green Transition Performance Evaluation Model Based on Digital Economy

Ying Yue[1,*]

[1] Business School, Zhengzhou University of Economics and Business, Zhengzhou 451191, Henan, China

SUMMARY: *In this paper, we first systematically select indicators from four dimensions, namely, financial, environmental, social and innovation, to build a framework for evaluating the performance of green transformation of enterprises. It integrates the mutation level method and entropy weight method, and at the same time introduces the cloud model to solve the conversion problem between qualitative evaluation and quantitative data. Taking the panel data of enterprise A from 2020 to 2024 as the empirical object, the results show that the innovation performance of enterprise A is the core driving force of transformation, with a weight of 0.3777. From a comprehensive point of view, the evaluation result of enterprise A's green transformation performance is "yellow (good)", close to "green (excellent)" and "green (good)". "Green (excellent)" grade, but there are structural differences among the dimensions.*

KEYWORDS: *green transformation performance evaluation; mutation level method; entropy weight method; cloud modeling*

1 Introduction

The rapid advancement of digital technologies presents new opportunities for corporate green transformation. Digital technologies can deeply integrate into every aspect of business operations, driving changes in production methods, enhancing resource utilization efficiency, reducing environmental pollution, and achieving coordinated economic and environmental development [1, 2]. Green supply chain management serves as a crucial pathway for corporate green transformation. Within the digital economy, enterprises leverage digital technologies to advance the upgrading of green supply chain management [3, 4]. Specifically, personnel can utilize blockchain technology to establish transparent, traceable supply chain information platforms. These platforms enable real-time monitoring of processes including raw material procurement, transportation, production processing, and sales, ensuring every stage of the supply chain meets green and environmental standards.

By applying IoT technology, enterprises can track carbon emissions in real time during logistics and transportation processes [5]. Subsequently, through intelligent dispatch systems, they can optimize transport routes and select more environmentally friendly transportation methods. For instance, prioritizing rail or electric freight transport while reducing the use of fuel-powered vehicles in road transportation can lower carbon emissions during the shipping process. Additionally, big data analytics can be leveraged to assess market demand and accurately forecast raw material usage, thereby preventing resource wastage caused by inventory buildup. Furthermore, enterprises can employ digital technologies for green product

*yyingbusiness@163.com
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innovation, developing environmentally friendly and resource-efficient products [6]. Specifically, digital design tools are employed to comprehensively consider the product lifecycle during the design phase. From raw material selection and production process determination to usage management and post-end-of-life recycling, green principles are upheld to minimize environmental impacts. Additionally, companies can leverage digital marketing to promote eco-friendly products and enhance consumer awareness and acceptance of green offerings [7]. Utilizing digital channels like social media and e-commerce platforms, businesses can communicate the environmental benefits and sustainability values of their products, guiding consumers toward green choices and thereby fostering the growth of the green consumption market [8].

Against the backdrop of corporate green transformation, establishing a scientific and comprehensive green transition performance evaluation system holds significant importance for promoting sustainable development in enterprises [9]. This system must comprehensively evaluate enterprises' green transition outcomes across economic, environmental, and social dimensions while emphasizing the intrinsic connections and synergistic effects among these dimensions [10]. By establishing appropriate evaluation indicators and weight allocations, it can provide precise decision support to guide enterprises in optimizing resource allocation, reducing carbon emissions, and enhancing social responsibility during their green transition [11].

The definition of green transformation for enterprises varies, but all share the core principle of pursuing environmental benefits through innovation, planning, green production, and other means to achieve sustainable development [12]. Multiple studies indicate that the digital economy significantly drives the green transformation of manufacturing. Si et al. [13] systematically analyzed the theoretical impact of the digital economy on corporate green transformation and formulated hypotheses. Their empirical research confirmed that the digital economy substantially empowers the green transformation of manufacturing. They noted that the digital economy enhances corporate green total factor productivity by strengthening innovation capabilities, improving the efficiency of factor mobility, and increasing corporate emission costs. Zhao et al. [14] discovered a significant positive relationship between the digital economy and the green innovation levels of heavily polluting enterprises, with absorptive capacity serving as a mediating variable. They concluded that heavily polluting enterprises can achieve green transformation at a certain level of digitalization. Sun et al. [15] mined panel data from Chinese A-share listed companies from 2011 to 2022, obtaining results consistent with the above. Additionally, they found that the integration of the digital economy with the real economy has a greater impact on the green transformation of state-owned enterprises than private enterprises, while the impact on large enterprises is insignificant. Ning et al. [16] highlighted that digital finance plays a dominant role in promoting corporate green transformation through the digital economy, with resource allocation efficiency acting as a mediating force. This influence is more pronounced for enterprises in high-polluting industries or regions with higher development levels. Chen et al. [17] employed fixed-effects and mediation models to explore the relationship between the digital economy and corporate green transformation. Their study indicates that the digital economy alleviates financing constraints, propelling enterprises—particularly those in high-pollution industries—toward sustainable practices. Li et al. [18] constructed a model linking the digital economy to green economic efficiency using 2011–2018 panel data from over 200 Chinese cities. Results indicate the digital economy significantly enhances regional green economic efficiency, with technological innovation playing a pivotal role. Wang et al. [19] examined the impact of the digital economy on the green transformation levels of enterprises across different regions in China. Their analysis of geographic regional heterogeneity revealed that the digital economy promotes green transformation among enterprises in eastern and central regions. Threshold effect tests further demonstrated that industrial structure upgrading exerts a significant nonlinear influence on enterprises' green transformation.

Existing literature has conducted in-depth theoretical research on the influencing factors, driving forces, and transformation pathways of green transition, establishing diverse evaluation indicator systems and models to assess the effectiveness and efficiency of green transition [20, 21]. Lin et al. [22] constructed a corporate green transition performance evaluation model from the perspective of green innovation efficiency. They found that corporate digitalization levels exert a significant positive effect on green innovation efficiency, while R&D subsidies for digital transformation influence corporate green innovation. Wang et al. [23] developed a corporate green transition performance evaluation model based on digital infrastructure, examining its impact from three dimensions: economic performance, green innovation, and environmental performance. Endogeneity and robustness analyses confirmed digital infrastructure's promotional role across these three performance areas, enriching the performance evaluation framework for corporate green transitions. Pan et al. [24] applied an evaluation model to examine the impact trends of gas chromatography technology on corporate green energy transition. Findings indicate that increased R&D expenditure, technological innovation, and financing constraints are key factors driving the technology's promotion of corporate green energy transition. Chen et al. [25] employed a dual machine learning approach to construct a comprehensive evaluation model for high-quality green transformation based on multiple environmental policies. They found that command-and-control, market-incentive, and public-participation environmental policies all promote corporate green transformation, with synergistic effects among policies further enhancing this promotion. Researching green transition pathways for enterprises in the digital economy context not only helps manufacturing enterprises enhance competitiveness and achieve sustainable development under new economic conditions but also holds significant implications for advancing the green upgrading of the entire manufacturing sector and promoting sustainable socioeconomic development [26, 27].

This paper firstly establishes the index system from four aspects of finance, environment, society and innovation, and determines the weights through entropy weight method. Combined with the mutation level method, the indicators are integrated and calculated. The cloud model is introduced to realize the comprehensive evaluation combining qualitative and quantitative. Take Enterprise A as an example to start the empirical analysis, and verify the applicability of the model through five-year panel data. Dimensionless processing and entropy weighting method are used to determine the weights of indicators, and mutation level model is used to calculate the comprehensive performance layer by layer. Based on the five-year performance calculation results, the dynamic evolution characteristics of performance in each dimension are analyzed. With the help of matlabR2020a, the green transformation performance evaluation of enterprise A is realized.

2 Construction of a model for evaluating the green transition performance of enterprises based on the digital economy

In the context of the synergistic promotion of the digital economy and the “dual-carbon” goal, the green transformation of enterprises has become a key path to realize a win-win situation for both high-quality economic development and ecological environmental protection. However, there is a lack of scientific and systematic evaluation tools to support the effectiveness of green transformation, and traditional performance evaluation focuses on a single financial dimension, making it difficult to comprehensively reflect the multi-dimensional value of green transformation empowered by digitalization. Existing evaluation methods are insufficient to portray the complex non-linear relationship between indicators, and there is a technical bottleneck in the integration of qualitative indicators and quantitative data. In this context, the construction of a green transformation performance evaluation model that fits the characteristics of the digital economy is a realistic need for enterprises to optimize their transformation strategies.

2.1 Selection of indicators

The basic framework of enterprise green innovation performance evaluation system is shown in Figure 1. Digital transformation can effectively promote the improvement of enterprise green innovation performance by optimizing the internal management process and improving the efficiency of information sharing.

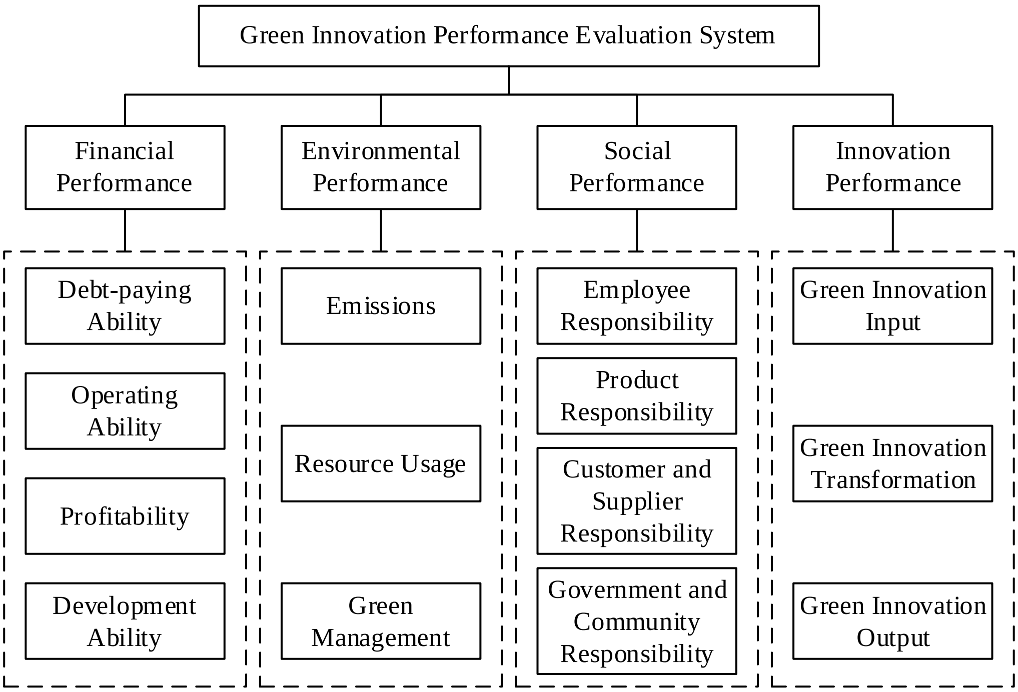

Figure 1: Basic Framework of the Performance Evaluation System

2.1.1 Selection of financial performance indicators

Financial performance indicators are selected as shown in Table 1. Financial performance is still crucial in green innovation performance evaluation, which is the most direct measure of the enterprise's operating results and economic interests, especially by shareholders and creditors. Good financial status is the cornerstone for enterprises to realize sustainable development, and financial performance evaluation is indispensable in green innovation performance evaluation.

Table 1: Selection of Financial Performance Indicators

Secondary indicator	Third-level indicator	Indicator formula
Debt repayment ability	Asset-liability ratio (%)	Total liabilities/Total assets
	Current Ratio (%)	Current assets/Current liabilities
Operating capacity	Accounts Receivable Turnover Ratio (times)	Total sales revenue/Average accounts receivable
	Inventory turnover rate (%)	Sales cost/Average inventory balance
Profitability	Return on Net Assets (%)	Net assets/Average net assets
	Net sales profit margin (%)	Net profit/Sales revenue
Development capability	Net asset growth rate (%)	(This year's net profit - Last year's net profit)/Last year's net profit
	Total asset growth rate (%)	(Total assets at end of period - total assets at beginning of period)/Total assets at beginning of period

2.1.2 Selection of environmental performance indicators

The environmental performance indicators are selected as shown in Table 2. Environmental performance reflects the performance and achievements of an organization or enterprise in environmental protection. Evaluating the environmental performance of an enterprise helps the enterprise to clarify its own shortcomings in environmental protection and then formulate corresponding improvement measures to enhance its environmental performance and realize sustainable development. Therefore, environmental performance must be included as an important part of green innovation performance evaluation.

Table 2: Selection of environmental performance indicators

Secondary indicator	Third-level indicator	Indicator formula
Emissions	Greenhouse gas emission density (tons per million yuan)	Total greenhouse gas emissions/Operating revenue
Resource utilization	Comprehensive energy consumption (tons of standard coal/ten thousand yuan)	Total energy consumption of the enterprise/Operating revenue
	Total water consumption density (tons per person)	Water resource usage/Total population
Green Management	Impact of business activities on the environment (thousand tons)	The fan products reduce carbon dioxide emissions

2.1.3 Selection of social performance indicators

The selection of social performance indicators is shown in Table 3. Social performance evaluation focuses on the assessment of the performance and results of an enterprise or organization in fulfilling its social responsibility. Conducting this evaluation helps enterprises to improve their social reputation and image and enhance social trust. The sustainable development theory advocates that enterprises must fulfill their economic goals while taking into account their social responsibilities. Stakeholder theory points out that corporate decisions affect shareholders, employees, customers, communities and other parties, and need to balance the demands of all parties. Incorporating social performance evaluation into green innovation performance evaluation can better promote the fulfillment of corporate social responsibility and achieve sustainable development and mutual benefit. When selecting social performance evaluation indicators, it is important to ensure that they are in line with the core values and strategic objectives of the enterprise. The selected indicators should comprehensively reflect the performance of the enterprise at the social level, so as to facilitate sustainable development and the fulfillment of social responsibility.

Table 3: Social Performance Evaluation Index System

Secondary indicator	Third-level indicator	Indicator formula
Product liability	Ratio of R&D personnel (%)	The data is sourced from the company's environmental, social and governance reports
	Research and Development Investment Ratio (%)	The data is sourced from the company's environmental, social and governance reports
Customer and Supplier Responsibilities	Customer Satisfaction Rate (%)	The data is sourced from the company's environmental, social and governance reports
	Accounts Payable Turnover Rate (%)	Sales cost/average accounts payable
Government and Community Responsibility	Total Tax Revenue (ten thousand yuan)	The data is sourced from the company's annual report

2.1.4 Selection of innovation performance indicators

The selection of innovation performance indicators is shown in Table 4. In today's sustainable business environment, innovation performance is subdivided into three important stages: green innovation input, green innovation transformation and green innovation output. In terms of enterprises' green innovation input, experts point out that enterprises' investment in innovation activities is not only a key force to achieve technological innovation, form competitive advantages and promote economic efficiency, but also has a crucial impact on enterprises' ability to enhance green innovation and performance. Green innovation can generate dual performance: first, direct performance, which is centered on the number of environmental patents owned by enterprises; and second, indirect performance, which can be measured with the help of parameters such as resource utilization efficiency and production efficiency. When discussing the transformation of green innovation, some experts pointed out that the improvement of enterprises' green innovation performance depends to a large extent on the new products developed through green patents. New products can not only stimulate the innovation vitality of enterprises, but also help to improve green innovation performance. Summarizing the above, the finalized innovation performance evaluation index system includes: on the input side, focusing on the proportion of enterprises' capital investment in green innovation activities; on the transformation side, considering the number of new green patents added by enterprises; and on the output side, combining diversified indexes such as economic, environmental and social benefits to comprehensively assess the innovation performance of enterprises.

Table 4: Selection of Innovation Performance Indicators

Secondary indicator	Third-level indicator	Indicator formula
Green innovation investment	Investment in research and development funds	Based on the amount of research and development investment and the intensity of research and development investment
Green innovation transformation	Green patent situation	Based on the number of green patents
Green innovation output	Economic benefits	Based on operating income, return on net assets, and the enterprise's financial reports
	Environmental benefits	Based on the corporate environmental, social and governance report
	Social benefits	Based on customer satisfaction, the situation of public welfare undertakings, as well as the corporate environmental, social and governance reports

2.2 Evaluation system construction

(1) Dimensionless processing of initial data

Due to the differences in the degree of change and units of the original data, it is necessary to judge the data before evaluating it with the mutation level method, whether it belongs to the positive or negative indicators before the dimensionless processing, so that each variable is in the $[0,1]$ interval of the data, so that the data is standardized, and the calculation formula is as follows:

Positive indicator:

$$O_{ij} = \frac{x_{ij} - \min(x_{1j}, x_{2j}, \ldots, x_{nj})}{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - \min(x_{1j}, x_{2j}, \ldots, x_{nj})} \tag{1}$$

Negative indicators:

$$O_{ij} = \frac{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - x_{ij}}{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - \min(x_{1j}, x_{2j}, \ldots, x_{nj})} \tag{2}$$

(2) Determine the weight of each evaluation index

In this paper, the weight of each indicator is sorted using the entropy weight method to determine the size of the degree of impression of each, so as to carry out comprehensive evaluation in a more reasonable way, using the entropy weight method formula as follows:

(1) After determining the importance of each indicator, calculate the weight of the j th indicator in the i th year of the indicator, the formula is shown below:

$$P_{ij} = \frac{z_{ij}}{\sum_{i=1}^{m} z_{ij}} \tag{3}$$

2) Calculate the information entropy E_j and utility value G_j for the j th indicator with the formulas shown below:

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} P_{ij} \cdot \ln P_{ij} \tag{4}$$

$$G_j = 1 - E_j, \left(1 \geq E_j \geq 0\right) \tag{5}$$

3) Calculate the weight W_j for each indicator using the following formula:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{m} 1 - E_j} \tag{6}$$

(3) Determine the mutation types at each level within the evaluation indicators and perform numerical calculations.

Under the mutation level system, if an indicator has only two sub-indicators, the system is considered a sharp-point mutation system; if an indicator can be decomposed into three sub-indicators, it is considered a swallowtail mutation system; if an indicator can be decomposed into four sub-indicators, the system is considered a butterfly mutation system. The formulas for the three most commonly used mutation type models are as follows:

Point mutation model: $f(Z) = Z^4 + aZ^2 + bZ$ (7)

Swallowtail mutation model: $f(Z) = \frac{1}{5}Z^5 + \frac{1}{3}aZ^3 + \frac{1}{2}bZ^2 + cZ$ (8)

Butterfly Mutation Model: $f(Z) = \frac{1}{6}Z^6 + \frac{1}{4}aZ^4 + \frac{1}{3}bZ^3 + \frac{1}{2}cZ^2 + dz$ (9)

The normalization formulas for the three mutation models after dimensionalization are as follows:

Point mutation model: $Z_a = a^{\frac{1}{2}}, Z_b = b^{\frac{1}{3}}$ (10)

Swallowtail mutation model: $Z_a = a^{\frac{1}{2}}, Z_b = b^{\frac{1}{3}}, Z_c = c^{\frac{1}{4}}$ (11)

Butterfly Mutation Model: $Z_a = a^{\frac{1}{2}}, Z_b = b^{\frac{1}{3}}, Z_c = c^{\frac{1}{4}}, Z_d = d^{\frac{1}{5}}$ (12)

(4) Conducting Comprehensive Performance Calculations

If indicators at the same level exhibit a correlation relationship, the “complementary” principle applies: the z value for that system is averaged across the control variables. If indicators exhibit a non-correlation relationship, the “take the smaller of the two” principle applies: the z value for that system is taken as the minimum among the control variables.

2.3 Cloud Model Construction

2.3.1 Cloud Model Concepts and Digital Characteristics

Cloud models typically leverage theories from probability theory and fuzzy mathematics to address the conversion between qualitative and quantitative concepts, which inherently involve uncertainty. They holistically describe the possibility and fuzziness between uncertain linguistic values and precise numerical values, enabling a seamless transformation between qualitative linguistic sets and quantitative data. The cloud model is primarily characterized by three numerical features: Ex, En, and He, representing the expectation (Ex), entropy (En), and hyperentropy (He), respectively. Among these, the expectation (Ex) represents the expected value of cloud droplet spatial distribution within a specific region. It serves as the core numerical feature in the cloud model, embodying the point most representative of the qualitative linguistic set. This expectation value reflects the anticipated distribution of cloud droplets in the designated area and can be interpreted as the central position or most probable value of the qualitative concept described by the cloud model. This expected value is typically determined through statistical analysis of extensive empirical data, reflecting the primary numerical characteristics of the qualitative concept. Entropy (En) quantifies the measurability of the qualitative concept; a larger En generally indicates a more macro-level concept. Simultaneously, entropy measures the uncertainty of the qualitative concept, determined by both the concept's probability and ambiguity. It reflects the dispersion of cloud droplets representing that qualitative concept. Hyperentropy (He) denotes the uncertainty measure of entropy—essentially the entropy of entropy—jointly determined by the concept's probability and ambiguity. It reflects the cohesion of each data value within a specific linguistic value range, i.e., the cohesion of cloud droplets. A higher hyperentropy indicates a more dispersed distribution of cloud droplets, greater cloud thickness, and increased model uncertainty. Conversely, a lower hyperentropy signifies a more concentrated distribution of cloud droplets, reduced cloud thickness, and diminished model uncertainty.

2.3.2 Algorithms for Cloud Models

The cloud model comprises two major algorithms: the forward cloud generator and the inverse cloud generator. The forward cloud generator generates cloud droplets based on known expected values (Ex), entropy (En), and hyperentropy (He), achieving a transformation from qualitative to quantitative data. The inverse cloud generator, conversely, analyzes existing cloud droplets to infer these three characteristic values, completing the quantitative extraction from quantitative samples to qualitative concepts. The algorithmic workflows for the forward and inverse cloud generators are illustrated in Figures 2 and 3, respectively.

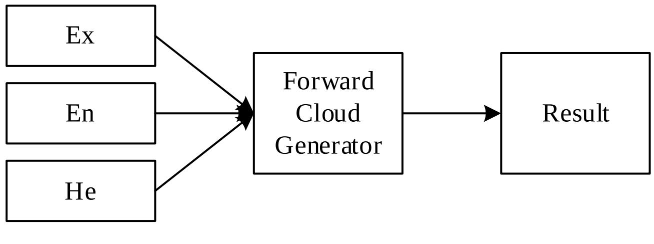

Figure 2: Forward Cloud Generator Algorithm

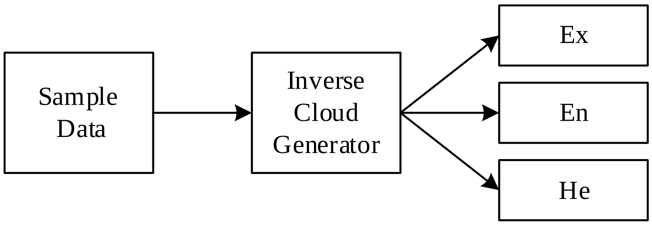

Figure 3: Reverse Cloud Generator Algorithm

2.3.3 Steps of the Cloud Model

Steps: Establish a set of evaluation criteria, defining five rating levels described as Excellent, Good, Average, Poor, and Very Poor. Each rating value falls within the interval $[C_{\min}, C_{\max}]$, constituting a bilateral constraint. Here, E_x is set to the midpoint of the interval range, calculated using formula (13), while E_n is set to $1/6$ of the interval range, calculated using formula (14). Here, $C_{\min}$ represents the lower bound of the rating set, and $C_{\max}$ represents the upper bound. H_e can be adjusted based on the inherent fuzziness of the rating itself, typically selected as a low-quantity value[65]. After multiple comparisons, setting $H_e = 0.05$ was found to be most suitable for this evaluation.

$$E_x = \left(C_{\max} + C_{\min}\right)/2 \tag{13}$$

$$E_n = \left(C_{\max} - C_{\min}\right)/6 \tag{14}$$

3 Empirical Analysis of Corporate Green Transition Performance Evaluation

3.1 Selection and Processing of Sample Data

3.1.1 Data Sources

This paper selects Company A as the research subject. Based on the established green transition performance evaluation system, financial performance sub-indicators are numbered A1–A8, environmental performance sub-indicators are numbered B1–B4, social performance sub-indicators are numbered C1–C5, and innovation performance sub-indicators are numbered D1–D5. Raw data for each indicator from 2020 to 2024 was collected from sources including Guotai An and corporate social responsibility reports, as shown in Table 5. From 2020 to 2024, Company A's debt-to-asset ratio decreased annually, while its current ratio and accounts receivable and inventory turnover rates rose continuously, indicating enhanced debt-repayment capacity and improved operational efficiency. Greenhouse gas emission intensity, comprehensive energy consumption, and water consumption per capita all showed downward trends, indicating improved resource utilization efficiency and initial success in green management. The proportion of R&D personnel and the R&D investment ratio continued to increase, while customer satisfaction rose annually. The company achieved synchronous growth in both investment and output in green innovation, demonstrating significant results in green transformation within the innovation dimension.

Table 5: Original Data of Each Indicator

Third-level indicator	2020	2021	2022	2023	2024
A1	56.23	54.86	53.13	51.75	50.32
A2	158.65	162.33	168.91	172.43	176.84
A3	7.25	7.82	8.51	9.16	9.63
A4	5.32	5.84	6.45	6.93	7.32
A5	8.51	9.12	9.81	10.55	11.24
A6	6.42	5.91	6.35	6.83	7.22
A7	6.13	6.87	7.53	8.19	8.75
A8	7.21	7.93	8.62	9.11	9.72
B1	0.85	0.82	0.78	0.74	0.70
B2	0.15	0.14	0.13	0.12	0.11
B3	28.52	27.92	27.13	26.41	25.85
B4	12.33	13.82	15.25	16.71	18.14
C1	12.55	13.13	13.82	14.57	15.26
C2	3.21	3.52	3.86	4.13	4.45
C3	86.54	87.21	88.02	88.85	89.54
C4	6.83	7.14	7.43	7.72	8.01
C5	12350.65	13484.66	14626.34	15895.42	17158.29
D1	2122.42	2353.28	2606.72	2852.44	3101.83
D2	15.16	18.35	22.11	26.74	30.25
D3	45000	48500	52300	56400	60200
D4	7.24	7.55	7.83	8.11	8.49
D5	8.12	8.35	8.67	8.92	9.26

3.1.2 Dimensionless Treatment

Due to differences in units and varying characteristics among the indicators, direct calculation is not feasible. Each indicator must undergo preprocessing. Since the standardized results may contain zero values, each indicator is shifted positively by 0.0001 units for computational convenience. The standardized results are presented in Table 6. The standardized outcomes for different indicators exhibit distinct variations, consistent with actual trends.

Table 6: Results of Data Standardization Processing

Third-level indicator	2020	2021	2022	2023	2024
A1	0.0001	0.2673	0.6375	0.7372	0.8501
A2	0.0001	0.3862	0.6326	0.8038	0.9001
A3	0.0001	0.2967	0.5863	0.7464	0.8422
A4	0.0001	0.3001	0.4822	0.6614	1.0001
A5	0.0001	0.3001	0.5275	0.7821	1.0001
A6	0.0001	0.3275	0.5473	0.7372	1.0001
A7	0.0001	0.3166	0.5501	0.7501	0.8801
A8	0.0001	0.3208	0.0062	0.0425	1.0001
B1	0.9001	0.8352	0.9001	0.9501	1.0001
B2	0.9037	0.8913	0.8504	0.9368	1.0001
B3	0.9163	0.8374	0.8364	0.9187	0.9836
B4	0.1037	0.3001	0.5624	0.7175	0.9017
C1	0.0001	0.0001	0.5375	1.0001	0.0001
C2	0.1185	0.3183	0.6853	0.8037	0.9001
C3	0.1286	0.3027	0.5863	0.7001	0.9519
C4	0.1175	0.3001	0.5973	0.7821	0.9307
C5	0.0001	0.3026	0.4275	0.2863	1.0001
D1	0.1863	0.3184	0.4863	0.7964	0.9307
D2	0.1172	0.3122	0.5185	0.7186	0.9364
D3	0.1084	0.3002	0.5372	0.7864	1.0001
D4	0.1175	0.3185	0.5017	0.8013	1.0001
D5	0.1426	0.3487	0.4973	0.7345	0.9375

3.2 Determining Indicator Weights Using the Entropy Weighting Method

Based on the preceding formula, the entropy values and utility values of each indicator were calculated, and the weights for each indicator were determined. The indicators were then ranked according to their weight values, with the results shown in Table 7. The tertiary indicators under Innovation Performance occupy the top four positions in weight distribution. Among these, Social Benefits within Green Innovation Output holds the highest weight (0.0836), with the cumulative weight of the four indicators reaching 0.3777. This indicates that innovation activities serve as the core driving force behind corporate green transformation. The indicator weights for Environmental Performance and Social Responsibility Performance are moderately ranked, while the weights for Financial Performance indicators are relatively low.

Table 7: Ranking of Indicator Weights

Primary indicator	Secondary indicator	Third-level indicator	Entropy value	Utility value	Weight	Sort
Financial performance	Debt repayment ability	A1	0.9037	0.0937	0.0191	22
		A2	0.9011	0.1002	0.0212	21
	Operating capacity	A3	0.9007	0.1053	0.0222	20
		A4	0.9002	0.1077	0.0238	19
	Profitability	A5	0.8999	0.1093	0.0266	18
		A6	0.8996	0.1104	0.0278	17
	Development capability	A7	0.8993	0.1132	0.0305	16
		A8	0.8991	0.1175	0.0307	15
Environmental performance	Emissions	B1	0.8927	0.1073	0.0543	6
	Resource utilization	B2	0.8935	0.1065	0.0508	7
		B3	0.8942	0.1058	0.0503	8
	Green Management	B4	0.8961	0.1039	0.0499	9
Social performance	Product liability	C1	0.8981	0.1019	0.0415	13
		C2	0.8985	0.1015	0.0412	14
	Customer and Supplier Responsibilities	C3	0.8972	0.1028	0.0421	11
		C4	0.8978	0.1022	0.0417	12
	Government and Community Responsibility	C5	0.8968	0.1032	0.0486	10
Innovation performance	Green innovation investment	D1	0.8911	0.1089	0.0654	5
	Green innovation transformation	D2	0.8884	0.1116	0.0713	4
	Green innovation output	D3	0.8832	0.1168	0.0829	2
		D4	0.8867	0.1133	0.0745	3
		D5	0.8821	0.1179	0.0836	1

3.3 Performance Calculation

Based on the weighting order obtained above, following the “complementary” and “non-complementary” principles, the X values for each level of indicators are calculated recursively using the normalization formula. If indicators within the same level exhibit strong correlation, the “complementary principle” is applied, using the average value of the sub-indicators as the value for the higher-level indicator. If indicators within the same level are weakly correlated, the “non-complementary principle” (i.e., “take the smaller value”) is applied, using the minimum value of the lower-level indicators as the value for the upper-level indicator. The results for each secondary indicator and average performance from 2020 to 2024 are shown in Table 8.

Within the financial performance dimension, debt repayment capacity demonstrated the most significant growth, steadily increasing from 0.6744 in 2020 to 0.8463 in 2024. In the environmental performance dimension, resource utilization efficiency achieved the strongest performance, with an annual average of 0.8944, rising rapidly from 0.8351 in 2020 to 0.9221 in 2024. Within the social performance dimension, customer and supplier responsibility demonstrated the fastest growth rate, increasing by 39.93%. The innovation performance dimension serves as the core driver of green transformation, with green innovation output standing out as the most prominent indicator, achieving an annual average value of 0.8056.

Table 8: Performance Calculation Results for 2020 - 2024

Secondary indicator	2020	2021	2022	2023	2024	Average value
Debt repayment ability	0.6744	0.7035	0.7375	0.8037	0.8463	0.7531
Operating capacity	0.7175	0.7364	0.7522	0.7638	0.7944	0.7529
Profitability	0.8185	0.8204	0.8271	0.8299	0.8342	0.8260
Development capability	0.5753	0.5973	0.6254	0.6361	0.6735	0.6215
Emissions	0.6372	0.6511	0.6862	0.7013	0.7214	0.6794
Resource utilization	0.8351	0.8937	0.9038	0.9173	0.9221	0.8944
Green Management	0.4832	0.4916	0.5163	0.5222	0.5284	0.5083
Product liability	0.5175	0.5353	0.5462	0.5715	0.5809	0.5503
Customer and Supplier Responsibilities	0.3922	0.4753	0.5012	0.5214	0.5488	0.4878
Government and Community Responsibility	0.4083	0.4164	0.4862	0.5018	0.5175	0.4660
Green innovation investment	0.4865	0.5018	0.5275	0.5726	0.5992	0.5375
Green innovation transformation	0.6183	0.6364	0.7863	0.8017	0.8264	0.7338
Green innovation output	0.6863	0.7484	0.8162	0.8735	0.9037	0.8056

3.4 Performance Evaluation

3.4.1 Establishing Evaluation Criteria Cloud

Considering the current state of green transition management at Company A, its green transition performance evaluation is categorized into four levels: U = {Red, Blue, Yellow, Green}, with corresponding score ranges [0,100]. Based on the aforementioned standard cloud model parameters, calculations were performed using the forward cloud generator in MATLAB R2020a to generate the standard cloud for Company A's green transition performance evaluation, as shown in Figure 4. Specifically: [0,60] indicates Company A's green transition performance is Red (Poor), [60,75] indicates Blue (Caution), [75,90] indicates Yellow (Good), [90,100] indicates Green (Excellent).

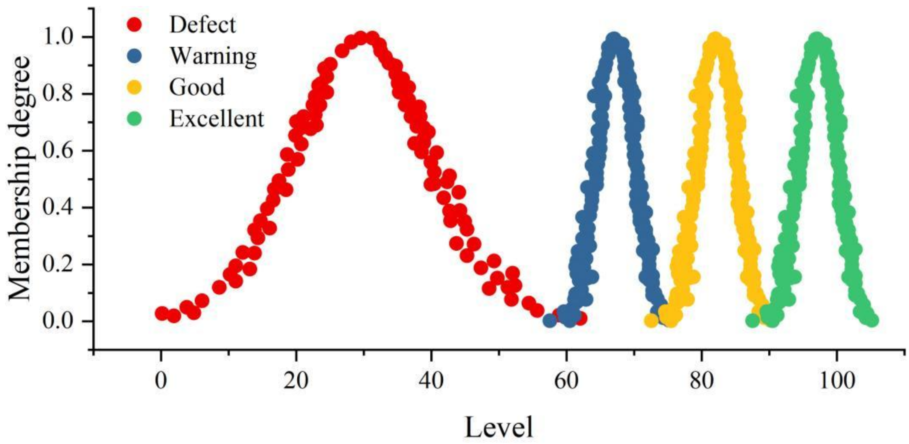

Figure 4: Cloud of Performance Evaluation Grade Standards

3.4.2 Evaluation Metric Cloud and Integrated Cloud

Further calculations of the cloud model characteristics were performed for the indicators, yielding the cloud model characteristic parameters (expectation, entropy, and hyperentropy) for all secondary indicators. The results are presented in Table 9.

The expected values of the cloud model for each secondary indicator ranged from 78 to 85, indicating an overall upper-middle level. This suggests that Company A has achieved certain results across all evaluation dimensions, though variations exist between dimensions. In terms of financial performance, profitability exhibited the highest expected value at 84.673. While the company's profitability level shows an overall positive trend, minor fluctuations occur between years. For environmental performance, the expected value of resource utilization efficiency is 82.473, with an entropy value of 0.576 and superentropy of 0.274. This indicates relatively stable evaluation results, highlighting the company's significant achievements in reducing energy consumption per unit of output and enhancing energy efficiency—a standout feature within the environmental dimension. For social performance, customer and supplier responsibility holds the highest expected value. However, its entropy and excess entropy reveal certain annual fluctuations. Regarding innovation performance, green innovation output—as the core tertiary indicator of innovation performance—has an expected value of 81.038 and a weight of 0.2410, making it the most heavily weighted among all secondary indicators. Its entropy and super-entropy values indicate relatively concentrated evaluation results with some dispersion, highlighting the company's sustained investment and achievements in green technology R&D and commercialization. This represents one of the most critical drivers propelling the company's green transformation.

Table 9: Feature Parameters of Cloud Model

Primary indicator	Secondary indicator	Weight	Cloud model characteristic parameters
Financial performance	Debt repayment ability	0.0403	(79.486,0.465,0.207)
	Operating capacity	0.0460	(80.586,0.286,0.411)
	Profitability	0.0544	(84.673,0.936,0.365)
	Development capability	0.0612	(78.352,0.845,0.213)
Environmental performance	Emissions	0.0543	(80.375,0.784,0.195)
	Resource utilization	0.1011	(82.473,0.576,0.274)
	Green Management	0.0499	(82.017,0.849,0.312)
Social performance	Product liability	0.0827	(83.582,0.762,0.176)
	Customer and Supplier Responsibilities	0.0838	(84.372,0.786,0.425)
	Government and Community Responsibility	0.0486	(79.371,0.664,0.282)
Innovation performance	Green innovation investment	0.0654	(80.475,0.963,0.136)
	Green innovation transformation	0.0713	(82.473,0.854,0.241)
	Green innovation output	0.2410	(81.038,0.927,0.195)

3.4.3 Analysis of Evaluation Results

Using the cloud model feature parameters for Company A's green behavior performance and the evaluation grade standard cloud model feature parameters obtained above, MATLAB R2020a was employed to plot the evaluation grade standard cloud and the comprehensive cloud

C within the same coordinate system. The comparison results between the comprehensive evaluation cloud and the standard cloud are shown in Figure 5. The “purple” region in the composite cloud map lies between “yellow (good)” and “green (excellent),” leaning closer to “yellow (good).” Therefore, Company A's green transformation performance evaluation result is “yellow (good).” Additionally, both the values and outliers in the composite cloud map are relatively small, indicating good stability and high validity in this evaluation.

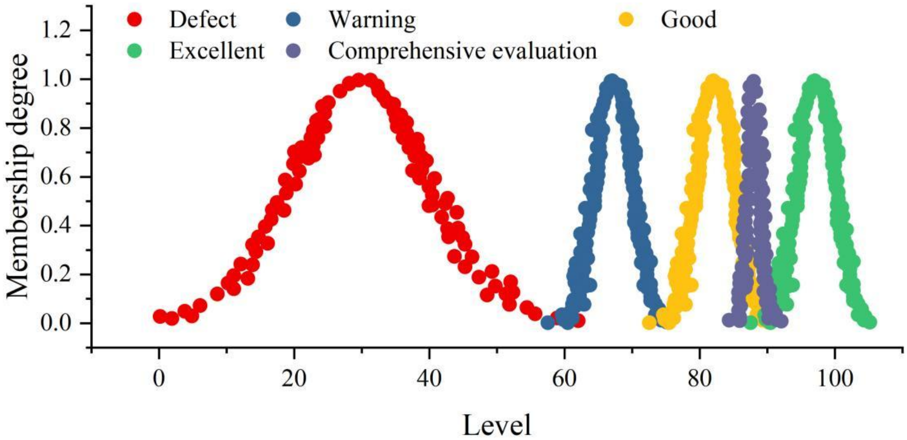

Figure 5: Comparison results of comprehensive evaluation cloud and standard cloud

4 Conclusion

This study systematically evaluated the effectiveness of Company A's green transformation in the digital economy context by constructing a performance evaluation model integrating four dimensions: financial, environmental, social, and innovation.

The tertiary indicators under innovation performance ranked highest in weighting, with social benefits in green innovation outputs carrying the highest weight (0.0836), totaling 0.3777 across all four indicators. Environmental performance and social responsibility indicators held intermediate weightings, while financial performance indicators exhibited relatively lower weights. Regarding financial performance, Company A demonstrated the highest expected value for profitability at 84.673. For environmental performance, the expected value of resource utilization efficiency was 82.473, with an entropy value of 0.576 and a super-entropy of 0.274. In social performance, customer and supplier responsibility had the highest expected value, but its entropy and super-entropy values indicated certain annual fluctuations. For innovation performance, green innovation output—a core tertiary indicator—has an expected value of 81.038 with a high weight of 0.2410. Its entropy and excess entropy indicate relatively concentrated evaluation results with some dispersion.

Overall, Company A's green transition performance evaluation is rated “Yellow (Good),” with both the value and excess value in the composite cloud map being relatively low.

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ORCID ID: 0009-0002-0364-498X

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