MULTI-DIMENSIONAL DRIVERS OUTLINING A NEW CARBON NEUTRAL BLUEPRINT FOR CHINA'S ENERGY COMPANIES

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Abstract. This research aims to reduce corporate carbon emissions and support China's carbon peaking and neutrality goals while generating economic benefits. Using the Delphi methods, this research identifies 23 factors across carbon accounting, green finance, and economic benefits. Through a hybrid DEMATEL-ISM-MICMAC-GREY methodology, this research analyzes the centrality and causality of these factors and prioritizes their relevance to economic benefits. A hierarchical model is developed based on their driving and dependence degrees. To ensure the objectivity of policy implication, the sample data selection relies on the 30 energy companies listed in the *2022 White Paper on the Competitiveness of New Energy Companies*. Chinese energy companies' results show the S_5 Benchmark is the sole foundational factor in the ISM model, determining the presence of other factors. Six-dimensional DEMATEL analysis clarifies intra-dimensional causal relationships and centrality degrees, while reciprocal interactions facilitate cross-dimensional partitioning via MICMAC. Linkage factors with the strongest system-wide interactions emerge as corporate decision-making focal points. Grey correlation analysis reveals intangible assets, financial assets, and return on sales exhibit the highest post-interaction correlations with economic benefits.
Keywords: *new carbon neutral blueprint, carbon accounting, green finance, economic benefits, DEMATEL-ISM-MICMAC-GREY model*

Introduction and literature

Scholarly investigations into the nexus among carbon accounting, green finance, and economic benefits have increasingly emerged in both domestic and international academic contexts. The long-term effects of various factors will indirectly affect ecological sustainability through channels such as corporate green behaviors, green technology R&D, and investment in green innovation (Hu et al., 2022). Green credit and other supportive financial policies enhance corporate financing efficiency, reduce capital costs, and foster economic growth. Most research findings on the nexus among the three perspectives emphasize positive or negative correlations in specific contexts. Nevertheless, expanding the economic value of companies is a systematic and holistic process. From a disciplinary perspective, accounting, finance, and economics are closely connected. Accounting serves as a foundational framework for recording commercial transactions in financing activities. Finance acts as a mechanism that provides companies with financial support for business operations and improves resource turnover efficiency. Economic benefit is the core goal of all commercial activities revolving around profit maximization.

Therefore, the interaction among carbon accounting, green finance, and economic benefit expansion can be conceptualized as a hierarchical model of synergistic effects. From previous research, this research identified 23 factors associated with six dimensions of

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corporate economic benefits. A hybrid model was developed to analyze the nexus among carbon accounting, green finance, and economic benefits using these factors. Based on these findings, this research establishes a scientific foundation for enhancing company profitability and promoting energy conservation and emission reduction as social benefits. Research hotspots in this field focus on the following aspects.

Impact of carbon quota on economic benefits

Previous research has focused on the control effect of carbon quotas. Jiang and Yang (2021) found that quota-based emission control promotes greater social welfare than carbon tax policies when companies obtain larger quotas. Researches have indicated that China's developed regions (e.g., Beijing, Tianjin, Jiangsu, and Shanghai) exhibit higher economic potential, whereas their counterparts (e.g., Shanxi, Liaoning, and Inner Mongolia) show lower economic potential owing to stringent emission regulations. Thus, the allocation of quotas directly influences the pace of economic growth (Yang and Lee, 2022; Zhou et al., 2023). Researches on the carbon market in China's power sector. It shows that potential economic output differs across carbon quota allocation principles, with sector-specific quotas driving growth when the electricity industry dominates the market (Wang et al., 2022).

Hence, an efficient carbon quota mechanism is necessary, involving the implementation of paid quota allocation and continuous improvement of quota accounting. Accurate quota accounting can mitigate quota misallocation and enable more scientific calculation of carbon emissions by electricity companies (Zhao et al., 2023). Accounting results can be classified as inventory, environmental assets, intangible assets, or financial instruments with trading rights. Different classification methods yield varied financial outcomes, which are interrelated and influence economic benefits. Some scholars classify carbon assets into six categories: carbon funds, carbon materials, carbon products, carbon credits, fixed assets, and intangible assets. Based on prior research and the accounting definition of assets, carbon assets have the potential to generate low-carbon value (Zhang et al., 2018).

Similarly, another research indicates carbon accounting enhances environmental awareness, though its promotion depends on top management commitment (Scaletti et al., 2025). This further suggests current carbon emission accounting measurement involves significant discretion, strongly influenced by senior executives' and relevant staff's will. Creating operational space for fraud and favoritism about profit manipulation via carbon emissions accounting.

The mediating effects of carbon credit for economic benefits

Carbon emissions serve as a mediator between high-quality green economic development and green credit. In regions with high economic development, the impact of green credit on high-quality green economic development has become more pronounced (Zhang et al., 2022). The environmental benefits and advantages of international carbon credit markets suggest that certain nations should allow domestic producers to purchase carbon credits in these markets. Establishing a global carbon credit market could significantly reduce worldwide emissions without compromising state sovereignty. Regarding economic benefits, carbon credit trading mobilizes capital to enhance economic scale. However, current regulations fail to directly curtail overall carbon emissions, and terminal policy solutions cannot tackle all existing environmental challenges.

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The carbon credit policy includes positive-incentive, reverse-punishment, and risk-management functions, which are crucial for enhancing corporate inclination toward eco-innovation. Moreover, through these functions, the policy can improve resource utilization efficiency (Chen et al., 2022). For cash-strapped companies, carbon credit risk affects the credit risk of the underlying companies through policy uncertainty, and spurs a positive correlation with economy (Zhang and Zhao, 2022). Green credit policies also directly support the application of clean technologies and optimization of production processes, thereby effectively enhancing total factor productivity (Ma and Li, 2025). The carbon credit benchmark offers a robust framework and clear guidelines, making policy execution smoother and more efficient. Furthermore, emission reduction in remanufacturing provides support to financially constrained companies. This support enables them to achieve dual objectives of economic benefit generation and environmental sustainability, thereby realizing a win-win scenario (Wang et al., 2022). Accordingly, S_5 Benchmark is a factor of carbon credit to improve economic benefits.

Potential economic benefits of carbon disclosure

Worldwide, the disclosure of carbon-related issues is increasing in political, social, academic, and practical significance (Velte et al., 2020). It has a negative effect on financial performance in the short term but a positive effect in the long term (Karim et al., 2021; Siddique et al., 2021). Enhanced carbon performance and consistent carbon information disclosure significantly boost company value growth. Large, high-market-value companies tend to disclose emissions more than smaller counterparts.

In contrast, due to negative impacts from profitability and leverage, highly profitable companies with heavy debt burdens tend to disclose less carbon emission information. In non-state-owned companies or those with advanced management, carbon emission disclosure contributes to enhancing economic growth (Yan et al., 2020). However, a negative correlation exists between carbon emission disclosure and disposable accruals, indicating that companies with more carbon information disclosure show better financial reporting quality (Bilal et al., 2022). Internal and external report information users are accountable for producing a high-quality financial report, which facilitates the companies' ability to get funding for expanding production.

Positive and negative effects of green finance on economic benefits

China's green finance development generally has a negative effect on bank loan issuance, with its impact magnitude on enhancing renewable energy investment efficiency being 0.0017 (He et al., 2019). When environmental policy uncertainty increases, macroeconomic conditions tend to deteriorate due to elevated environmental policy uncertainty. Such deteriorations cause the relationship between environmental policy uncertainty and carbon emission trading prices to turn negative (Wang et al., 2022). However, GMM results show that fintech, green finance, and total natural resource management have negative and significant impacts on GDP, whereas environmental benefits are significantly positively correlated with GDP (Zhou et al., 2024). Significant polluters also have exhibited heterogeneous responses to environmental policies, with both illegal pollution and green innovation on the rise. Green credit regulations substantially hinder the financialization of highly polluting companies, where financing constraints act as a transmission mechanism between illegal pollution and green innovation. Moreover, environmental policies drive companies to adopt green innovation and enhance total factor

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productivity. Furthermore, the Green Credit Guidance (GCG) exerted a more pronounced impact on small-sized enterprises, chief executive officers (CEOs) with financial expertise, and regions characterized by lower levels of financial development (He and Liu, 2023; Jiang et al., 2022; Kong et al., 2022; Li et al., 2023).

Green finance exerts a substantial influence on green energy in regions with high green economic growth. The development of green finance has a positive effect on the wind energy and photovoltaic power industries. Green finance also significantly enhances regional economic resilience, and the level of market integration amplifies the positive effect of green finance (Wei, 2024). Previous research employing mediation effect models has demonstrated that green credits exert a significantly negative impact on environmental pollution. In this relationship, environmental pollution functions as a mediator between green credits and the development of a high-quality green economy. This model reveals a transmission channel of "green credit → environmental pollution → high-quality development of the green economy" (Li et al., 2022; Zheng et al., 2022).

In certain regions, social welfare and manufacturer profits are complementary, with governments encouraging manufacturers to pursue collective welfare through the implementation of differentiated carbon emission quotas (An et al., 2021). In particular, after the publication of the Green Credit Guideline (GCG), corporate social responsibility increased significantly among companies covered by the GCG relative to non-covered peers. Moreover, restricted companies with significant environmental, social, and governance (ESG) improvements experienced higher market valuations and revenues. In addition, these companies engaged in more pro-environmental behaviors (e.g., green innovation) and incurred fewer environmental penalties (Li et al., 2022). With the strengthening of the Green Credit system, the interaction between the Green Credit Policy (GCP) and PM2.5 has confirmed the long-term beneficial impact of GCP on PM2.5. As a leading indicator, air quality allows companies to anticipate changes in bank credit preferences and adjust their financing strategies. Non-compliant green credit inhibits companies' green technological innovation, whereas compliant green credit has no impact on such innovation (Su et al., 2022).

Green bonds not only meet specified investment objectives but also augment the impact of climate change and environmental initiatives while fostering investors' social awareness of these issues (Jin et al., 2020). Reputational benefits, market signals for green bond issuance, and the ambition to address climate change are the primary drivers behind green bond issuance, motivating companies to adopt green bonds as a strategic option. As companies access the green bond market, they increasingly leverage green bonds to transform business models for profitability. However, they also recognize that green bonds incur higher issuance costs compared to comparable debt instruments (Sangiorgi and Schopohl, 2023).

During periods of market volatility, the correlation between carbon futures yields and the green bond index yield is the strongest and most pronounced. The green bond index exhibits the highest hedging efficacy against carbon futures risks and maintains robust performance even during economic crises. As a result, numerous investment companies have integrated green bonds into their investment portfolios as a strategic measure to mitigate overall losses (Dong et al., 2023). In contrast, the returns of green bonds and low-carbon stocks increase independently or move in the opposite direction. When included in a low-carbon portfolio, green bonds also offer diversification benefits (Reboredo et al., 2022). Green bonds represent investments in government and private projects that promote energy efficiency and economic growth (Zhao et al., 2022).

Green finance management brings about economic benefits

The effect of carbon pricing on the economy is underpinned by individual attitudes toward it. Distributing carbon dividends through carbon tax revenue raises the incomes of the poorest households while reducing redistribution among individuals with similar income levels (Fremstad and Paul, 2019). As tax levels increase, public support for carbon taxes decline, though support among those favoring lump-sum dividend payments is less affected by higher rates (Sommer et al., 2022). Citizens often perceive carbon pricing as driven solely by budgetary objectives, overlooking how it shapes incentives for low-carbon consumption and production. This phenomenon occurs primarily because the acceptability of carbon taxes largely depends on political trust.

Higher levels of economic development correlate with public opposition to carbon taxes, while greater carbon intensity predicts public support for such taxes (Levi, 2021; Tang and Yang, 2023). Under equivalent GDP impacts, carbon taxes exhibit greater proportional emission reduction efficiency than carbon trading, with this benefit amplifying over time. Imposing a carbon tax on energy companies immediately increases industry costs and domestic energy goods prices (Jia and Lin, 2020). Therefore, investigating the effects of carbon pricing on economic benefits requires an analytical approach that balances generality and specificity.

Financial performance represents economic benefits

In research on the impact of carbon performance on financial performance, Accounting-based indicators exhibit enhanced explanatory power for corporate green actions (Ganda, 2017). Carbon emission mitigation exhibits a positive linear correlation with return on sales (ROS), indicating that reduced emissions correlate with a linear increase in ROS. This positive linear relationship assumes that ROS is used to measure profitability. However, a negative correlation exists between carbon emission mitigation and Tobin's Q. Most notably, carbon performance improvements exhibit a negative linear correlation with stock market performance (Lewandowski, 2017). Reducing carbon emissions boosts return on assets (ROA), return on equity (ROE), and return on sales (ROS) but has minimal impact on Tobin's Q and the current ratio. Higher accountability scores are associated with greater ROA. For ROA and ROS, the relationship is linear, whereas for ROE, the association between carbon emission reduction and corporate financial performance (CFP) is curvilinear. Carbon emission reductions enhance short-term profitability as measured by ROA, ROE, and ROS but have minimal impact on Tobin's Q (van Emous et al., 2021).

On average, a 0.1% increase in carbon efficiency correlates with a 1% rise in profitability and a 0.6% decline in systemic risk (Trinks et al., 2020). And another research found that financial metrics indicate a NPV of $623.7 million, a discounted payback period of 9.4 years, and a ROI of 1.53 times. Replacing a conventional thermal power plant of equivalent capacity reduces carbon dioxide emissions by nearly 115,000 tons annually. This replacement results in an approximate 82% reduction in lifecycle emissions, demonstrating substantial environmental benefits (Nadeem et al., 2026).

In summary, scholarly inquiry into the effects of carbon accounting and green finance on economic benefits largely focuses on positive or negative correlations under specific conditions. Carbon accounting credits originate from surpluses or deficits in carbon quotas. These credits are traded to adjust emission costs for companies with excessive carbon emissions and meet capital needs for environmentally conscious companies that reduce

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carbon emissions. This trading aims to eliminate negative environmental externalities and enhance the efficiency of environmental resource utilization. Research on carbon accounting disclosures, centered on companies fulfilling their social responsibilities, examines how different property rights structures impact financial performance. Ultimately, corporate commercial operations should not be divorced from their financial implications.

Concurrently, significant advancements have been achieved in both the diversification of green financial products and the economic benefits generated by managerial practices. Prior research has identified both positive and negative correlations between carbon emissions and financial metrics such as return on sales (ROS), return on equity (ROE), return on assets (ROA), and Tobin's Q. This reflects the direct manifestation of carbon-related economic benefits in financial performance indicators. For now, preliminary research findings remain largely general.

To address existing research gaps, this research aims to resolve the deficiency in prior literature by precisely quantifying the relationships and impact magnitudes among the key factors of carbon accounting, green financing, and economic benefits. Building on these quantified insights, the research develops a 23-factor, six-dimensional, and detailed nexus model to further elucidate the complex interconnections among these dimensions, with the significance of causal relationships clarified within the hierarchical model. Existing data on the operational practices of Chinese energy companies acknowledge the centrality of energy conservation.

Materials and methods

Determination of research methods

The adoption of the DEMATEL-ISM-MICMAC-GREY integrated research method stems from the necessity to achieve the research objectives, specifically that energy companies are typical benchmarks in energy conservation and emission reduction. This research aims to explore the internal operational mechanisms through which energy companies contribute to the achievement of carbon neutrality goals in the dimensions of carbon accounting, green finance, and economic benefits.

DEMATEL can identify the direct and indirect interrelationships among factors, clarify the key driving factors and affected factors in the system, and lay a relational foundation for subsequent hierarchical analysis. The interactions among the 23 factors in energy companies are precisely derived through the DEMATEL analysis. ISM is capable of addressing the challenges of "disordered system structure and ambiguous factor hierarchy" and intuitively presenting the hierarchical influence relationships between factors. In addition to the known more about interactions among the 23 factors, their hierarchy is obtained through ISM, which further clarifies the internal mechanism of their functioning.

MICMAC can categorize factors into four types: autonomous factors (low driving force, low dependence), dependent factors (low driving force, high dependence), linkage factors (high driving force, high dependence), and driving factors (high driving force, low dependence). Further classifying each factor through MICMAC helps leverage the characteristics of different types of factor groups. GREY addresses the pain of "insufficient data or ambiguous information" in practical research. Due to the small number of top-tier and representative Chinese energy companies, the adoption of GREY can make up for this deficiency.

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Based on existing research on the impact of carbon accounting and green finance on economic benefits, both carbon accounting and green finance exert positive effects on the economy. As presented in *Table 1*, this research identified 23 relevant influencing factors for further analysis of their interrelationships. 20 experts were surveyed via questionnaires to assess the degree of mutual influence among factors, using a scoring scale where 0 indicates unfamiliarity, 1 denotes no impact, 2 signifies minor impact, 3 represents moderate impact, and 4 indicates significant impact.

Table 1. *Factors from previous researches*

Target	Dimensions	Factors	Units	Sources
S_{23} economic benefits	Carbon quota	S_1 Inventory	Yuan	Huang et al. (2020); Halat et al. (2021); Krecl et al. (2022); Zhang et al. (2022); Marchi and Zanoni (2023)
		S_2 Intangible assets	Yuan	Song et al. (2023)
		S_3 Financial instruments	Yuan	Xie et al. (2021)
		S_4 Environmental assets	Yuan	Díaz-Chao and Ficapal-Cusí (2021); Demiralay et al. (2023)
	Carbon credit	S_5 Benchmark	-	Anjos et al. (2022); Chen et al. (2022); Zhang and Zhao (2022); Wang et al. (2022); Velvizhi et al. (2023); Dumrose and Höck (2023)
	Carbon disclosure	S_6 Disclosure policy	-	Velte et al. (2020); Siddique et al. (2021); Ma et al. (2023); Long et al. (2023)
		S_7 Disclosure content	-	Wegener et al. (2019); Linares-Rodríguez et al. et al. (2022)
		S_8 Disclosure mode	-	Karim et al. (2021); Liu and Zhang (2022)
		S_9 Audit and verification	-	Qian et al. (2018); Zhang et al. (2020); Bosu et al. (2023); Kang et al. (2023)
	Green finance	S_{10} Carbon trade	Yuan	Wang et al. (2022); Liu et al. (2021); Tang et al. (2022); Zhang et al. (2024)
		S_{11} Carbon credit loans	Yuan	An et al. (2021); He et al. (2023); Kong et al. (2022); Li et al.(2023); Su et al. (2022); Li et al.(2022); Zheng and Zhang (2023); Jiang and Yang (2021); He et al. (2019)
		S_{12} Carbon bond	Yuan	Ren et al. (2022); Li et al. (2022); Dong et al. (2023); Hu et al. (2022); Zhao et al. (2022); Su et al. (2022)
		S_{13} Carbon fund	Yuan	Rohleder et al. (2022); Amighini et al. (2022); Naqvi et al. (2021); Bhutta et al. (2022)
	Green finance management	S_{14} Carbon trust	Yuan	A Retrospective of the World Bank's Experience with Select Climate and Carbon Trust Funds (2020)
		S_{15} Carbon tax	Yuan	Gilbert E. Metcalf (2021); Sebastian Levi (2021); Jia and Lin (2020); Sommer et al. (2022); Fremstad and Paul (2019); Yang and Tang (2023); Hu et al. (2025)
		S_{16} Carbon financial products	Yuan	Zhang et al. (2018); Chevallier et al. (2021)
	Financial performance	S_{17} Equity assets	Yuan	Wu et al. (2022); Su et al. (2022)
		S_{18} WACC	Yuan	Gohdes et al. (2022)
		S_{19} ROE	Yuan	Sun et al. (2020)
		S_{20} ROA	Yuan	Ma and Kuo (2021); van Emous et al. (2021); Fortune Ganda (2018); Stefan Lewandowski (2017)
		S_{21} ROS	Yuan	Stefan Lewandowski (2017)
		S_{22} Tobin's Q	Yuan	Stefan Lewandowski (2017); Yan et al.(2020); Benkraiem et al. (2022); Dong et al. (2022); Trinks et al. (2020); Siddique et al. (2021)

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A total of 20 questionnaires were distributed, with 13 valid ones retrieved and 7 invalid ones excluded. The questionnaire structure is based on the 23 identified factors, requiring experts to conduct a circular scoring of the degree of mutual influence between each pair of factors. For example: $S_1 \rightarrow S_1$, $S_1 \rightarrow S_2$, ..., $S_1 \rightarrow S_{23}$; $S_2 \rightarrow S_1$, $S_2 \rightarrow S_2$, $S_2 \rightarrow S_3$, ..., $S_2 \rightarrow S_{23}$. Namely, $S_{23} \rightarrow S_1$, ..., $S_i \rightarrow S_{i-n}$, ..., $S_i \rightarrow S_{i-1}$, $S_i \rightarrow S_i$, $S_i \rightarrow S_{i+1}$, ..., $S_i \rightarrow S_{i+n}$, ..., $S_{23} \rightarrow S_{23}$. Herein, $1 \leq i \leq 23$, $1 \leq I + n \leq 23$, and $1 \leq i\text{-}n \leq 23$. First, financial data were identified including total profit, investment income from financial instruments, financial assets, inventory, intangible assets, total borrowings, ROE, ROA, and *ROS* from *2018* to *2021*. These data were then extracted from the financial reports and social responsibility disclosures of the 30 companies listed in the *"2022 White Paper on the Competitiveness of New Energy Companies"* for analysis. Based on the availability and completeness of the data, they are Contemporary Amperex Technology Co., Ltd, GCL System Integration Technology Co., Ltd, Longi Green Energy Technology Co., Ltd, China Energy Construction Group Co., Ltd, Power Construction Corporation of China, Ltd.

Delphi

The Delphi method is a structured expert consultation strategy. To ensure the objectivity of research outcomes, this research distributes questions to experts who operate anonymously and independently. Typically, the number of experts is limited to up to 20. In this research, the mean value of these experts' evaluations was determined. Expert A serves as a Doctoral Supervisor and Dean at the School of Finance and Economics, Shanghai University of Finance and Economics (SUFE). Expert B is an Assistant Professor of Economics at the University of International Business and Economics (UIBE), holding a bachelor's degree from Tsinghua University and master's and doctoral degrees from the University of Michigan, USA. Expert C works as a Master's Supervisor and Assistant Dean at the School of Finance, Guangdong University of Foreign Studies (GDUFS). Expert D, a doctoral degree holder, is affiliated with Postal Savings Bank of China (PSBC) and serves as Secretary-General of the Youth Federation. Expert E holds multiple roles including Bank President, Deputy General Manager of a Central State-owned Enterprise, and Expert of the Evaluation Committee for Yunnan Provincial Government-Guided Fund for Equity Investment, with the professional title of Senior Economist (Professor-level). Expert F is President of China Construction Bank (CCB) and holds a part-time master's degree. Expert G, a master's graduate from Nanyang Technological University (NTU) in Singapore, acts as Investment Research Manager at Shenzhen High-Tech Investment Group Co., Ltd. Expert H serves as Investment Research Manager in the Investment Banking Department of Fudian Bank's Head Office; He holds a master's degree from Southwestern University of Finance and Economics (SWUFE) and holds the title of Senior Accountant. Experts I, J, and K are Managers at Huadian New Energy Group Co., Ltd. Expert L, a doctoral degree holder, is an Independent Scholar in Singapore, Professor at Nanyang Technological University (NTU), and an entrepreneur. Expert M, a Master of Engineering from Chongqing University, holds concurrent positions as Director of the Foreign Economic and Trade Department, Director of the Research and Development Department at Sichuan Aerospace Technology Research Institute, and Deputy General Manager of Sichuan Aerospace Materials Company.

DEMATEL

The Decision-making Trial and Evaluation Laboratory (DEMATEL) integrates graphical and matrix tools to assess logical and causal relationships among factors in

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complex systems, as proposed by Battelle Memorial Institute between 1972 and 1976 (Emilio et al., 1974). By constructing a direct influence matrix of logical relationships among all system factors, DEMATEL determines the impact degree of each factor on others, enabling the assessment of centrality and causality. These quantified influence degrees, centrality, and causality form the basis for model development. Consequently, each factor's causal correlation and systemic position are identified (Soares et al., 2023). The DEMATEL method has limitations in addressing uncertain scenarios, managing information gaps, and resolving conflicts among experts. It also cannot express ambiguous values around discrete metrics (Bai and Sarkis, 2013). In this research, 13 experts were surveyed via questionnaires, with results collected using the Delphi method.

Step 1: Establish the initial direct influence matrix $A = (a_{ij})_{m\times n}$, where a_{ij} denotes the influence degree of factor i on factor j. This matrix characterizes the direct influence relationships among all factors. To further explore the correlation of indirect effects across factors, computing the exhaustive influence matrix is imperative. After deriving the normalized direct influence matrix F, the exhaustive influence matrix K is determined. Specifically, the most significant value C is identified by comparing the row and column totals of the initial direct influence matrix A. The normalized direct influence matrix F is then obtained by normalizing each element of A with C. Following the equation:

$$F = A/c \tag{Eq.1}$$

Step 2: Standardize the direct influence matrix by

$$\mathrm{c} = \max\left[\max_{1\le j\le n}\sum_{i=1}^{m} a_{ij}, \max_{1\le i\le m}\sum_{j=1}^{n} a_{ij}\right] \tag{Eq.2}$$

Step 3: Determine the exhaustive influence matrix K

$$K = \lim_{m\to\infty}(F + F^2 + F^3 + ...F^m) = F(E\text{-}F)^{-1} \tag{Eq.3}$$

Step 4: Compute the row centrality and column causality from the comprehensive influence matrix K, following the sequences specified in *Equations 4*, *5*, *6* and *7*. Herein, r_i denotes the comprehensive influence degree exerted by factor i on other factors, while c_i represents the comprehensive influence degree imposed on factor i by other factors. $r_i + c_i$ is the centrality of factor i, the larger the value of centrality is, the greater role of this factor can be in the system. Moreover, if r_i-$c_i > 0$, the factor is categorized into the cause group; conversely, if r_i-$c_i < 0$, it falls into the effect group.

$$\begin{cases} (r_i)_{n\times 1} = \left[\sum_{j=1}^{n} k_{ij}\right]_{n\times 1} & \text{(Eq.4)} \\ (C_i)_{1\times n} = \left[\sum_{i=1}^{n} k_{ij}\right]_{1\times n} & \text{(Eq.5)} \end{cases}$$

$$\text{Centrality} = \mathrm{r_i} + \mathrm{c_i} \tag{Eq.6}$$

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$$\text{Causality} = r_i - c_i \qquad \text{(Eq.7)}$$

ISM-MICMAC

Walter Field, a J.N. professor in the United States, established the ISM model (Interpretive Structural Model) in 1973 to research the framework of complex social and economic systems. It decomposes the complex system into numerous subsystems (factors). It builds a multi-level hierarchical structure model by using the accumulated practical experience and expertise of humans through the auxiliary function of a computer program. It decomposes the complex system into numerous subsystems. It builds a multi-level hierarchical structure model using the accumulated practical experience and expertise of humans and the auxiliary function of a computer program (Vishwakarma et al., 2022; Zhao et al., 2019). It is appropriate for system analysis with various factors, complex relationships, and unclear structure, and it can also be utilized for competition schemes and other domains.

The MICMAC analysis approach employs the notion of matrix multiplication to estimate the driving degree and dependence degree. This research classified the factors as autonomous, dependent, independent, and linkage factors based on the computation of the final reachable matrix and the results of the degree of dependence. Each category represents a varying level of dependence and driving.

Step 1: The adjacency matrix is defined as:

$$B_{ij} = \begin{cases} 0 \; k_{\mathrm{ij}} < \gamma \\ 1 \; k_{\mathrm{ij}} \geq \gamma \end{cases} \qquad \text{(Eq.8)}$$

γ is set to 0.5

$$D = (B + I)^{n+1} = (B + I)^{n} \neq (B + I)^{n-1} \neq B + I \qquad \text{(Eq.9)}$$

Step 2: Compute reachability matrix D for reachability set $R(S_i)$, antecedent set $A(S_i)$, common set $C(S_i)$, beginning set $B(S_i)$, ending set $E(S_i)$;

Step 3: Compute the row sums and column sums of the reachable matrix. The row sum is defined as the driving degree, representing the extent to which a factor influences other factors. The column sum is denoted as the dependence degree, indicating the extent to which a factor is affected by other factors.

Step 4: Construct graph of MICMAC method.

Grey correlation

Grey correlation analysis explores the specific degree of correlation between the change and development of distinct grey system factors. By processing the score information, it is possible to clarify the degree of correlation between various influencing factors and the system. Identify the significant factors affecting the system from incomplete information, thereby providing a foundation for companies to improve the economic benefits of decision-making (Soares et al., 2023). After normalizing the values of the parent and comparative series, the difference sequence may be determined. Two-stage minimum difference and the two-stage maximum difference can then advance one step. The intended result of the grey correlation research is the grey correlation coefficient (Wu, 2022). Comparing with DEMATEL, which is subjected to expert judgments,

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incomplete information, and uncertainty (Gan et al., 2022). The grey correlation theory can complement this owning to its capacity to figure out uncertainty problems, such as discrete data and incomplete information (Liu et al., 2021).

Step 1: Determine the parent series and comparative series. The basic idea of grey correlation analysis is to evaluate the correlation degree by analyzing the influence of the comparative series on the parent series. The parent series refers to the data series reflecting the characteristics of the system behavior, and the comparative series refers to the data series composed of factors affecting the system behavior.

Parent series:

$$x_0\ (k) = \{x_0\ (1), x_0\ (2), ..., x_0\ (n)\}$$

Comparative series:

$$x_1\ (k) = \{x_1\ (1), x_1\ (2), ..., x_1\ (n)\}$$

$$x_2\ (k) = \{x_2\ (1), x_2\ (2), ..., x_2\ (n)\}$$

$$x_m\ (k) = \{x_m\ (1), x_m\ (2), ..., x_m\ (n)\}$$

Step 2: Normalize the initial value to ensure the equality and homogeneity of each factor, dimensionless and normalized transformation must be performed prior to correlation analysis. The greatest value of i for all factors in the initial information is $x_i(max)$, while the minimum value of i is $x_i(min)$. After normalization, this research acquires dimensionless parent series $y_0(k)$ and comparative series

$$y_i(k)\ (i = 1,2,...,m; k = 1,2,...,n)$$

among them,

$$y_i(k) = \frac{x_i(k)\text{-}x_i(min)}{x_i(max)\text{-}x_i(min)} \quad \text{(Eq.10)}$$

Step 3: Compute the series of difference values, including the two-stage minimum and maximum differences. The difference series is defined as the sequence representing the absolute differences between each comparative series and the parent series. Specifically, the two-stage minimum difference refers to the minimum value among the minima of the absolute difference series, while the two-stage maximum difference denotes the maximum value among the maxima of the difference series.

Difference series:

$$\Delta_i(k) = \left|y_0(k)\text{-}y_i(k)\right|\ (i = 1,2,...,m) \quad \text{(Eq.11)}$$

Two-stage minimum difference:

$$\min_i \min_k \Delta_i(k) = \min_i \min_k \left[y_0(k)\text{-}y_i(k)\right] = \alpha \quad \text{(Eq.12)}$$

Two-stage maximum difference:

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$$\max_i \max_k \Delta_i(k) = \max_i \max_k \left[y_0(k)\text{-}y_i(k)\right] = b \ (i = 1,2,...,m,\ k = 1,2,...,n) \quad \text{(Eq.13)}$$

Step 4: Compute the grey correlation coefficients between influence factors x_1, x_2, ...,x_m and total profit x_0. $\xi_i(k)$denotes the correlation coefficient between the indicator K of sample i and the optimal indicator. ρ is the discrimination coefficient, introduced to mitigate overvaluation distortion, where $\rho = \max_i \max_k \Delta_i(k)$. The value range of ρ is (0,1), with ρ = 0.5 commonly adopted, the correlation coefficient is computed as:

$$\xi_i(k) = \frac{\min_i \min_k [y_0(k)\text{-}y_i(k)] + \max_i \max_k \rho[y_0(k)\text{-}y_i(k)]}{|y_0(k)\text{-}y_i(k)| + \rho \max_i \max_k [y_0(k)\text{-}y_i(k)]} = \frac{\alpha + \rho b}{|y_0(k)\text{-}y_i(k)| + \rho b} \quad \text{(Eq.14)}$$

Step 5: To determine the grey correlation degree, the correlation coefficient—measuring the association between each influencing factor (comparative series) and total profit, it may be used to examine the relationship between the two factors (parent series). Complex data and scattered information hinder global comparability, thus, the average value is typically employed to quantify the correlation degree between influencing factors and total profit. A correlation degree closer to 1 indicates a stronger relationship. For *i = 1, 2, ..., n,*

$$\gamma_i = \frac{1}{2} \sum_1^n \xi i(k) \quad \text{(Eq.15)}$$

Step 6: Series correlation degree. Based on the correlation series used to identify the correlation degree of profit-influencing factors, a higher correlation degree indicates a closer relationship between the factors and the system. The specific values of correlation degrees and their ranking can best characterize the correlation level among factors. Put the comparative series in order of correlation degree to the same parent series and mark it as $\{x\}$, If $\gamma_{0i} > \gamma_{0j}$ means that for the same parent series $\{x_0\}$, the influence of $\{x_i\}$ on parent series is greater than that of $\{x_j\}$.

Step 7: A hierarchical model is constructed by taking $C(S_i) = R(S_i)$ as standard and combining the research results of DEMATEL, ISM, MICMAC and grey correlation.

Results

The research results of DEMATEL

Using the Delphi method, questionnaires to thirteen experts quantify the mutual impact of each factor from academic institutions, banks, and financial organizations. Following questionnaire collection, mean scores for 529 questions were computed and transformed into Matrix A (direct influence matrix), as presented in *Table A1*. The values in the table reflect the average of the thirteen experts' individual assessments. Upon computing the comprehensive influence matrix, the indirect influence relationships among factors can be identified.

Comprehensive-influence matrix

As shown in *Table A2*, computing the direct influence matrix A to obtain its comprehensive influence matrix K. The data of comprehensive influence matrix K describe the indirect influence relationship among multiple factors. r_i. To determine the centrality

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and causality degrees of each factor, the row sums of the comprehensive influence matrix *K* and *B*, the column sums, were initially computed. Adding up r_i and c_i to compute the centrality. The higher the value, the greater the effect and significance of this factor in relation to the remaining 22 factors. Subtract r_i and c_i to obtain the causality degree, as indicated in *Table 2*, which is positive, suggesting that this factor has a greater impact on other factors. This is a particularly helpful information to have, as there are numerous instances of centrality in which to differentiate the relative importance of system factors. As the centrality of S_3, S_4, S_7, S_9, S_{10}, S_{11}, S_{13}, S_{16}, S_{20} and S_{21} exceeds 10, these factors are the most significant in the entire factor system. Among these key factors, the green finance dimension accounts for three, namely S_{10}, S_{11}, and S_{13}. This indicates that the green finance dimension exerts the most positive influence among the six dimensions.

Table 2. *Centrality and causality*

Factor	r_i	c_i	Centrality	Causality
S_1	5.25	4.52	9.78	0.73
S_2	5.04	4.23	9.27	0.82
S_3	5.48	5.02	10.50	0.46
S_4	5.52	4.98	10.49	0.54
S_5	5.40	3.86	9.26	1.54
S_6	5.13	4.66	9.79	0.47
S_7	4.68	5.82	10.50	-1.14
S_8	3.69	4.33	8.01	-0.64
S_9	4.95	5.31	10.26	-0.36
S_{10}	5.65	5.84	11.50	-0.19
S_{11}	4.65	5.78	10.43	-1.12
S_{12}	4.54	4.94	9.48	-0.40
S_{13}	5.61	5.31	10.92	0.31
S_{14}	2.85	4.46	7.31	-1.60
S_{15}	4.29	4.42	8.70	-0.13
S_{16}	4.84	5.43	10.27	-0.59
S_{17}	4.81	4.40	9.21	0.42
S_{18}	4.88	4.51	9.38	0.37
S_{19}	5.08	4.69	9.77	0.40
S_{20}	5.54	5.66	11.20	-0.11
S_{21}	5.88	5.12	11.01	0.76
S_{22}	4.53	5.05	9.58	-0.52

Negative causality indicates that other factors influence the factor. In *Table 2*, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{14}, S_{15}, S_{16}, S_{20}, and S_{22} have negative causality. When it comes to correlation, the aforementioned factors influence each other. For Causality > 0, there are $S_1 = 0.73$, $S_2 = 0.82$, $S_5 = 1.54$, $S_{13} = 0.31$, $S_{18} = 0.37$, $S_{19} = 0.40$, and $S_{21} = 0.76$. Among them, S_5 has the largest causality value of 1.54, making it a core causal factor with the most significant driving effect on other factors. Efforts should be focused on leveraging the driving role of S_5 in energy companies, and only by setting clear benchmarks can other factors exert their positive effects effectively.

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For Causality < 0, there are $S_7 = -1.14$, $S_8 = -0.64$, $S_9 = -0.36$, $S_{10} = -0.19$, $S_{11} = -1.12$, $S_{12} = -0.40$, $S_{14} = -1.60$, $S_{15} = -0.13$, $S_{16} = -0.59$, $S_{17} = 0.22$, $S_{20} = -0.11$, and $S_{22} = -0.52$. Among them, S_{14} has the smallest causality value of -1.60, serving as a core result factor with the strongest dependence on other factors. S_5 is the most critical causal factor, driving changes in multiple factors; S_{14} is the most critical result factor, being most affected by other factors. Through the distinction of causality, the roles of various factors in the system can be clarified. Causal factors should be the focus of intervention, and optimizing these factors can promote the realization of carbon neutrality in energy companies. Result factors should be the focus of monitoring, and attention should be paid to their state changes after being affected to prevent the occurrence of environmental degradation risks.

Computation result draws the network diagram of each dimension's effect relationships according to the centrality degree and causality degree in *Table 2*. As depicted in *Figures 1–5*, the beginning of the arrow represents the influencing factor, while the point of termination represents the affected factor.

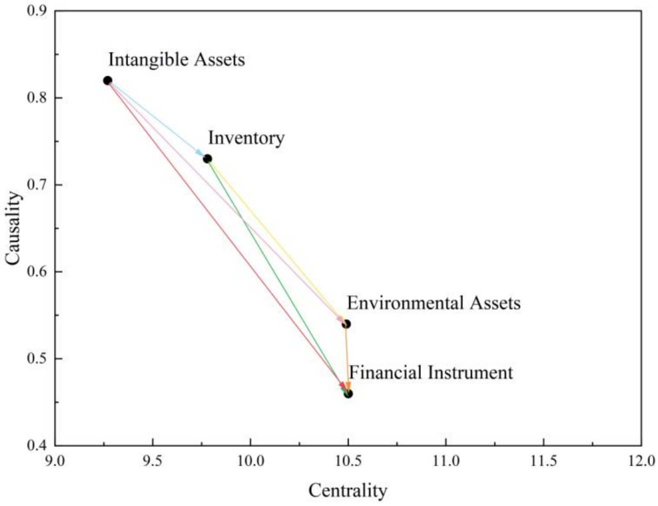

Figure 1. *Dimension of carbon quota on accounting*

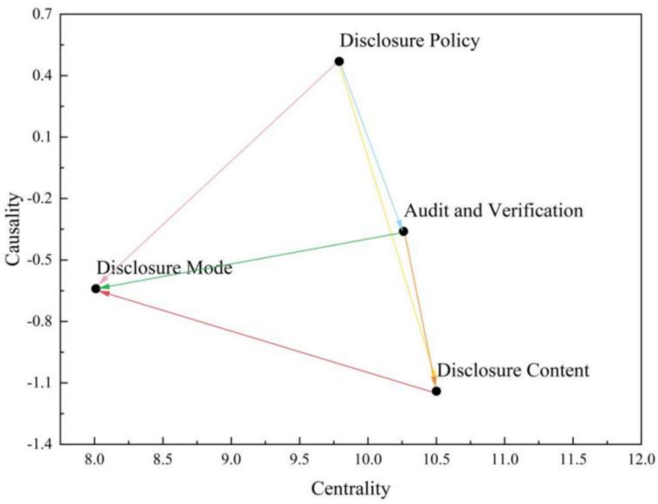

Figure 2. *Dimension of carbon accounting disclosure*

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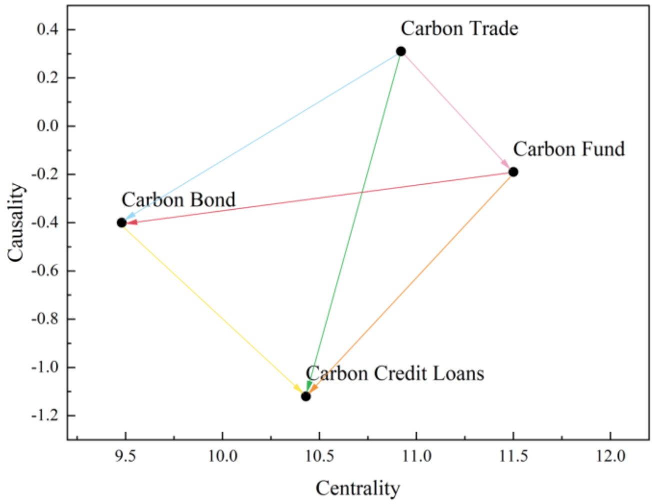

Figure 3. *Dimension of green finance*

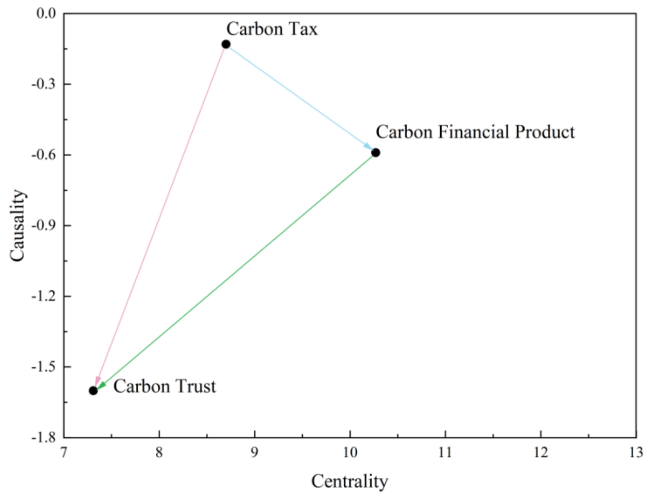

Figure 4. *Dimension of green finance management*

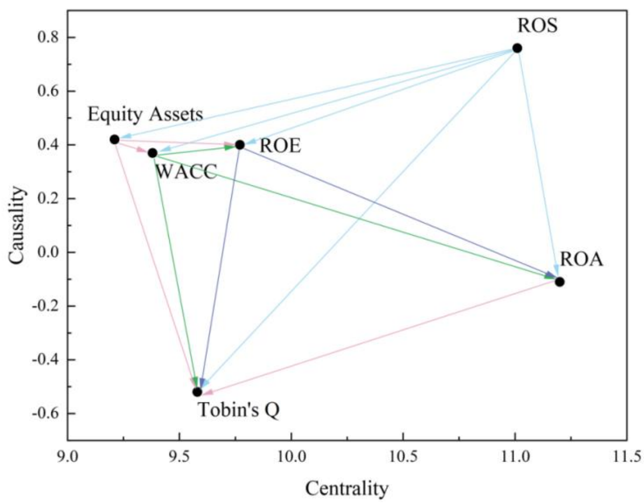

Figure 5. *Dimension of financial performance*

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The research results of ISM-MICMAC

Conducting factor analysis is to determine the influence of each factor on economic benefit and how the causal relationships between factors manifest at different levels. Building on the 22 factors outlined above, this research incorporates S_{23} economic benefits into the development of the ISM model. And this research regards MICMAC analysis as a methodology for identifying the extent of mutual influence among factors.

Initial reachability matrix

Set the practical threshold value to 0.5, and use the Boolean operation of *Equations 9* and *10* to generate the reachable matrix *M*, as shown in *Table A3*.

Influence factors set

The reachable set $R(S_i)$ of the reachable matrix M is produced by program operation, antecedent set $A(S_i)$, common set $C(S_i)$, beginning set $B(S_i)$, ending set $E(S_i)$ of the Matrix M are shown in *Table A4*. The first level of the target hierarchical model can be found by computing $C(S_i) = R(S_i)$. Eliminate the rows and columns to which the first level belongs, then computing the rest levels of the target hierarchical model bases on the same process $C(S_i) = R(S_i)$ as shown in *Table A4*. Finally, a preliminary hierarchical structure of all factors can be established. However, mere factor interconnections are insufficient to fully elucidate whether a factor acts as an active influencer or a passive recipient of influence from other factors.

Dependence and driving degree

Based on the dependence degree and driving force of each factor, *Figure 6* is divided into four regions: Autonomous Factors, Dependent Factors, Linkage Factors, and Driving Factors. In the Autonomous Factor region, both the dependence degree and driving force are weak; notably, no factors are present in this region. In the Dependent Factor region, the values of the horizontal and vertical axes differ: the driving degree is weak, while the dependence degree is strong. In this region, S_{18}, S_{19}, S_{20}, S_{21}, S_{22} and S_{23} are all dispersed. In the region characterized by the linkage factor, both dependence and driving degrees are high. Specifically, 16 factors exhibit identical values of dependence and driving degree in this region. S_1, S_2, S_3, S_4, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, are converged at the same point. In the Driving factor region, the driving degree is significant, while the dependence degree is weak. *Table A5* and *Figure 6* demonstrate that just one factor occurs in this region.

The research results of grey correlation

Given that the application of the initiative of energy conservation and environmental protection to accounting and finance is still in its infancy. The impact of carbon accounting and green finance on economic benefits can be investigated through grey correlation analysis of energy companies. In the *"2022 White Paper on the Competitiveness of New Energy Companies"*, the top five listed Chinese energy companies are ranked. This research compiled data for these companies from their annual and social responsibility reports during 2018 to 2021. Research data includes information on investment income from financial instruments, financial assets, inventory, intangible

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assets, total borrowings, return on equity (ROE), return on assets (ROA), and return on sales (ROS). In this research, collected data serve as comparative series to assess the correlation between factors and green economic benefits, and derive relevant conclusions.

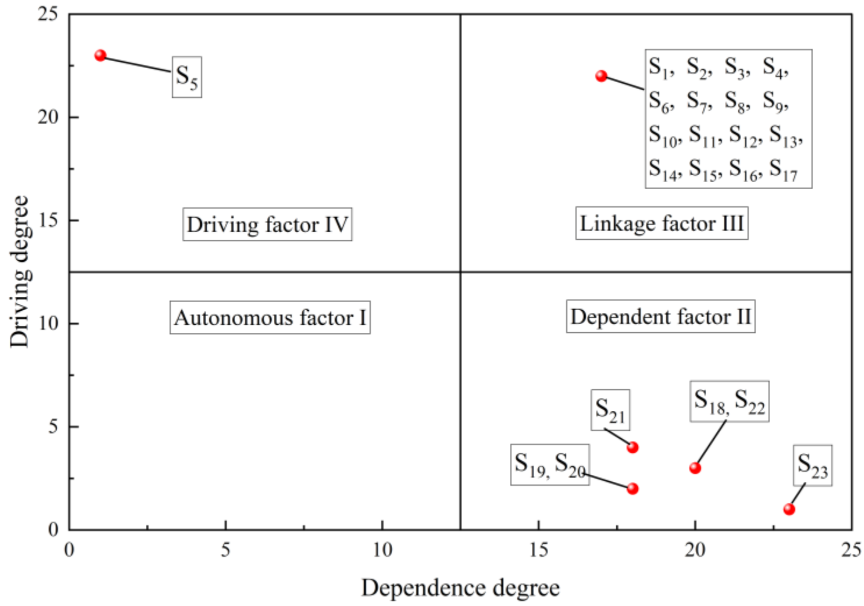

***Figure 6.** Driving and dependence degree of 23 factors*

Computation of correlation

Parent series:

$$x_0(k) = \{6896000000,6881000000,7375000000,9869000000\}$$

Comparative series:

$$x_1(k) = \{2715425246, 2767265347, 1467921908, 2539395127\}$$

$$x_2(k) = \{2211895418, 3786700663, 7757759692, 6725073300\}$$

$$x_3(k) = \{40417283457,47317727191,29654956550,28171292116\}$$

$$x_4(k) = \{28644534435, 39776700722, 40975510301, 45742063432\}$$

$$x_5(k) = \{63559359717,76943322660,54855929397,54795611836\}$$

$$x_6(k) = \{0.052,0.090,-0.039,0.041\}$$

$$x_7(k) = \{0.018,0.035,-0.006,-0.007\}$$

$$x_8(k) = \{0.393,0.086,0.199,0.160\}$$

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where x_0 denotes total profit, x_1 represents investment income from financial instruments, x_2 stands for financial assets, x_3 indicates inventory, x_4 signifies intangible assets, x_5 refers to total borrowings, x_6 is Return on Equity (ROE), x_7 is Return on Assets (ROA), and x_8 is Return on Sales (ROS). Following normalization, the dimensionless results are presented in *Table 3* and *Figure 7*.

This research created *Table 4* by computing the absolute difference series between each comparative series and parent series.

Table 3. *Normalized matrix*

Year	Total profit	Investment income of financial instruments	Financial assets	Inventory	Intangible assets	Total borrowing	ROE	ROA	ROS
2018	0.005	0.960	0	0.640	0	0.396	0.712	0.616	1
2019	0	1	0.284	1	0.651	1	1	1	0
2020	0.165	0	1	0.078	0.721	0.003	0	0.035	0.366
2021	1	0.825	0.814	0	1	0	0.625	0	0.241

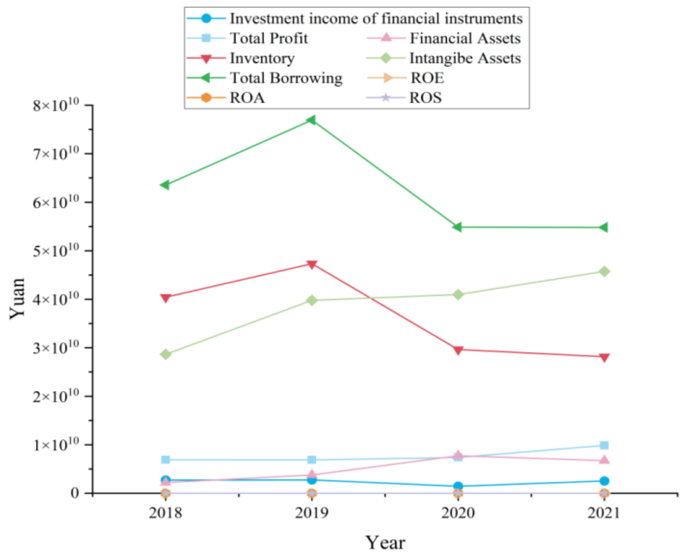

Figure 7. *Trend comparison of energy listed companies*

Table 4. *Difference series*

Year	Investment income of financial instruments	Financial assets	Inventory	Intangible Assets	Total borrowings	ROE	ROA	ROS
2018	0.955	0.005	0.635	0.005	0.391	0.706	0.611	0.995
2019	1	0.284	1	0.651	1	1	1	0
2020	0.165	0.835	0.088	0.556	0.163	0.165	0.130	0.201
2021	0.175	0.186	1	0	1	0.376	1	0.759

Ranking of grey correlation coefficient

Create a list of grey correlation coefficients as the final step. Intangible assets correlate most strongly with the total profit of the parent series, followed by financial assets and return on sales (ROS).

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The nexus model of factors

Through the investigation of multiple factor combinations and verification, a hybrid model developed using empirical data from representative companies. *Figure 8* depicts the internal causal relationships among carbon accounting, green finance, and economic benefits. It can be a clarification how these components interact to achieve the predefined economic benefit objectives. The illustration also demonstrates the relative significance of specific factors within the overall system. Highlighting their influence on the complex interplay among carbon accounting, green finance, and economic benefits in pursuit of the established goal. Additionally, it illustrates the active and passive roles of each factor and the overlapping interaction pathways through which they contribute to achieving the top-level objective.

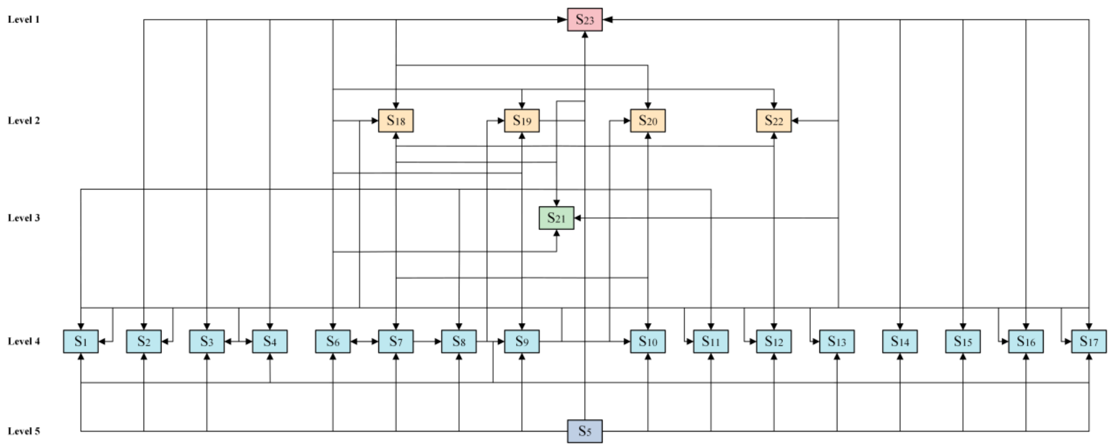

Figure 8. *The hybrid model of factors*

Discussion

The researchers employed a mixed-methods approach combining qualitative and quantitative techniques to analyze existing research and recent data from new energy companies. Through this analysis, 23 key factors were identified within the domains of carbon accounting, green finance, and economic benefits. Subsequent analysis was performed to derive more precise data, including the magnitude and significance of their impact on economic benefits.

Nexus of factors

DEMATEL analysis

As shown in *Table 2* and *Figures 1–5*, various dimensions exhibit distinct degrees of centrality and causality. In the Carbon Quota dimension, *Table 2* and *Figure 1* indicate that S_4 Environmental Assets has the highest centrality, followed by S_3 Financial Instruments, while other factors show relatively lower centrality. When carbon quotas are accounted for as S_4 Environmental Assets or S_3 Financial Instruments in the accounting system, they play a pivotal role in driving economic benefits. Conversely, neither S_4 Environmental Assets nor S_3 Financial Instruments attains a causality degree comparable to their centrality levels. Thus, the causality degrees by which S_4 Environmental Assets and S_3 Financial Instruments influence S_{23} Economic Benefits do not equate to the

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centrality degrees by which they affect other factors. Given that the profitability of fixed carbon assets reflects, to some extent, the profitability of low-carbon assets (Zhang et al., 2018), recording carbon accounting as environmental assets substantially impacts the carbon quota dimension.

Existing findings suggest that an equity-based carbon quota allocation system is more suitable for China's national context than efficiency-based and principle-based carbon quota allocation schemes (Zhou et al., 2023). The current carbon quota system's imperfections lead to voluntary carbon performance measurement and disclosure using multiple criteria. Consequently, management discretion is helpful for carbon performance transparency (Velte et al., 2020).

In Carbon Credit dimension, a centrality score of 9.26 and a causality score of 1.54 demonstrate that S_5 Benchmark significantly influences S_{23} Economic Benefits and other-dimensional factors.

In the Carbon Disclosure dimension, S_7 Disclosure Content exhibits the highest centrality, followed by S_9 Audit and Verification and S_6 Disclosure Policy, while S_8 Disclosure Mode shows relatively lower centrality. This ranking reflects their descending influence on S_{23} Economic Benefits. However, their influence on other factors remains less prominent, with only S_6 Disclosure Policy demonstrating positive causality and the rest showing negative causality. To evaluate the quality of companies' carbon emission accounting disclosure, these factors require close attention.

In the Green Finance dimension, S_{10} Carbon Trade exhibits the highest centrality across all dimensions, significantly surpassing other factors. This indicates that a well-established carbon trading market and robust carbon trading activities profoundly impact the enhancement of economic benefits. Within the Green Finance dimension, S_{13} Carbon Fund and S_{11} Carbon Credit Loan rank second and third, respectively, with their influence on economic benefits moderately weaker than that of S_{10} Carbon Trade. Noting that S_{13} Carbon Fund exhibits positive causality, it has a relatively significant impact on other factors. To support corporate low-carbon operations and energy conservation, policymakers have introduced more favorable green finance regulations. However, given that China's financial industry environment is not yet fully developed, green finance must prioritize completing the institutional framework for the carbon trading market and enhancing the efficiency and consistency of corporate carbon trading activities.

In the Green Finance Management dimension, each factor influences only economic benefits, without affecting other factors. Among these, S_{16} Carbon Financial Products has the strongest influence on economic benefits, followed by S_{15} Carbon Tax and then S_{14} Carbon Trust.

In the Financial Performance dimension, S_{20} ROA and S_{21} ROS exert a relatively significant impact on economic benefits, with centrality scores exceeding 11. Across all factors, only three achieve this threshold, underscoring the critical importance of prioritizing S_{20} ROA and S_{21} ROS to maximize their positive influence on economic outcomes while mitigating potential declines from oversight. Notably, S_{20} ROA exhibits the most pronounced divergence between centrality and causality, with positive centrality and negative causality, indicating a strong direct impact on economic benefits but minimal influence on other factors. This aligns with prior research demonstrating that carbon emission disclosure positively correlates with ROA (an accounting-based factor) and negatively correlates with MVA (a market-based factor) (Ganda, 2017).

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ISM-MICMAC analysis

By referencing the values of the reachable matrix D in *Table A3* and the set of influencing factors of the reachable matrix *Table A4*, the hybrid model was sequentially applied to generate the reachable set $R(S_i)$, antecedent set $A(S_i)$, and common set $C(S_i)$. Subsequently, Level 1 to Level 5 were established, respectively. Inferences from Level 5 indicate that the benchmark is the sole underlying factor at the most fundamental level. Additionally, S_4 Environmental Assets and S_5 Benchmark exert direct effects on all other factors. The benchmark quantity set for each company ensures that system participants incur no additional carbon costs for production and operation activities within the benchmark range. Only when actual carbon emissions exceed the benchmark are companies required to reserve or obtain sufficient offset credits. Otherwise, they face economic penalties imposed by system administrators. Thus, the benchmark dictates the existence of other factors.

The fourth level contains S_1, S_2, S_3, S_4, S_5, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, forming the most concentrated aggregation layer. S_1 Inventory exerts a broad impact on S_3 Financial Instruments, S_4 Environmental Assets, S_7 Disclosure Content, S_{10}Carbon Trading, S_{11}Carbon Credit Loan, S_{13} Carbon Fund, S_{14} Carbon Trust, S_{16} Carbon Financial Management, S_{19} ROE, S_{20} ROA, S_{22} Tobin's Q and S_{23} Economic Benefits. If carbon accounting is recorded as inventory, such inventory may qualify as a financial instrument. In accordance with the accounting standards for environmental assets, inventory is also classified under asset accounts. Carbon inventory disclosure directly affects the content of carbon accounting information reports. When accounted for as inventory, carbon trading, which is centered on this carbon inventory, maintains a close connection with carbon credit loans and carbon funds that are established to facilitate corporate green financing. However, some existing research findings present distinct perspectives. The development of green finance reduces the short-term loan limits for renewable energy companies and weakens the contingent governance role of short-term loans in renewable energy investment. Thereby lowering the efficiency of renewable energy investment (He et al., 2019). If carbon is reported as inventory, companies may also conduct carbon trust asset management or monetized financial investment management. In accordance with the accounting standards for the preparation and analysis of financial statements, carbon inventory is reflected in financial indicators such as ROE, ROA, and Tobin's Q, directly impacting the achievement of economic benefits. Carbon efficiency is correlated with resource efficiency and affects financial performance, particularly in mitigating systemic risks (Trinks et al., 2020).

Moreover, the deep-level factors, the one with the largest number of factors (the fourth level) is not only influenced by the fundamental factors level (the fifth level) but also has an impact on both the transitional factors level (the second level and the third level) and the surface-level factors (the first level). The third level S_{21} ROS and the second level S_{18} WACC, S_{19} ROE, S_{20} ROA, S_{22} Tobin's Q serve as the intermediate levels of the entire system, primarily influencing the S_{18} Capital Cost WACC and the S_{23}ROA, which can be verified through the financial index equation for WACC. Nevertheless, the influence of the level beneath the third level is more prominent.

The second level comprises S_{18}, S_{19}, S_{20}, and S_{22} associated with the capital-cost-related factors of WACC, ROE, ROA, and Tobin's Q. The S_{18} WACC as a metric for capital cost, exerts an influence on S_{22} Tobin's Q and S_{23} Economic Benefits. The quantitative relationship between the weighted average cost of capital (WACC) and Tobin's Q serves to illustrate the impact that the capital cost has on Tobin's Q represented

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by WACC. This influence stems primarily from accounting standards and the principles governing financial indices. The overarching objective is to maximize the first level S_{23} Economic Benefits. The hierarchical structure model constructed using the Interpretive Structural Modeling (ISM) methodology delineates the hierarchical influence relationships among the 23 factors.

However, the above analysis fails to elaborate on the degree of influence and its significance to the overall model system. The MICMAC method remedies this deficiency by categorizing factors into four types: autonomous, dependent, linkage, and independent factors. As shown in *Figure 6*, the autonomous factor category in this system contains no factors, indicating that none of the 23 factors both affects the entire system and is influenced by other factors.

S_{18} WACC, S_{19} ROE, S_{20} ROA, S_{21} ROS, S_{22} Tobin's Q, S_{23} Economic Benefits fall into the category of dependent factors, characterized by relatively concentrated distribution and strong degrees of both driving force and dependence. S_{18} WACC, S_{19} ROE, S_{20} ROA, S_{21} ROS and S_{22} Tobin's Q exert an impact on total profit and the achievement of the ultimate goal of S_{23} Economic Benefits. Furthermore, these factors are heavily influenced by other dimensions, which aligns with the concept of accounting treatment. Specifically, based on the records and reports of accounting measurement, the financial performance of the remaining factors can be evaluated through specific indicators, thereby reflecting their financial quality.

In terms of linkage factors, S_1 Inventory and S_2 Intangible Assets are classified as S_1 and S_2, respectively. S_3 Financial Instruments, S_4 Environmental Assets, S_6 Disclosure Policy, S_7 Disclosure Content, S_8 Disclosure Mode, S_9 Audit and Authentication, S_{10} Carbon Trading, S_{11} Carbon Credit Loans, S_{12} Carbon Bond, S_{13} Carbon Fund, S_{14} Carbon Trust, S_{15} Carbon Tax, S_{16} Carbon Finance Management, S_{17} Equity Assets are centralized in a specific place. As *Table A5* shows, the driving and dependence degrees are equivalent, constituting the factor group with the highest interaction intensity within the entire system framework. This should serve as the primary focus of company decision-making and the direction for policy formulation.

In the zone of independent factors, there is just one factor S_5 Benchmark with a significant driving degree and a weak degree of dependence. Serving as the foundation of the structural model, the S_5 Benchmark underpins other factors, explaining its strong driving power and independence from other factors. Establishing this benchmark represents a critical foundation that companies and relevant functional departments must carefully address.

Grey correlation analysis

Through integrated DEMATEL-ISM-MICMAC analysis, this research presents the interrelationships and mutual influence intensities among system components in the computation results. Additionally, it also presents the significance and role of each factor in understanding the overall structural model. In China, however, research on carbon accounting and green finance development remains in its infancy, with practical implementation also in an exploratory stage. Approximately 18.2% of companies disclosed carbon-related information in their social responsibility reports, indicating that companies need to place greater emphasis on carbon information disclosure (Yan et al., 2020). The 23 energy-saving and consumption-reduction factors have been functioning in the company's operations. The DEMATEL-ISM-MICMAC findings neither identify

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the factors contributing to carbon emissions doubling nor quantify the linkage intensity between these factors and the achievement of corporate profits.

Therefore, this research selects the financial and social responsibility reports disclosed by the top 30 Chinese companies listed in the *"2022 White Paper on the Competitiveness of New Energy Companies"*. It then extracts data corresponding to 23 factors from each annual report, including total profit, investment income from financial instruments, financial assets, inventories, intangible assets, total debt, return on equity (ROE), return on assets (ROA), and return on sales (ROS). Grey correlation analysis is conducted under conditions of incomplete information.

According to *Figure 7*, the investment income on financial assets and financial instruments follows a trajectory comparable to that of the total profit, which is steady and fluctuates slightly. The change of other factors and the pattern of the total profit gap's change are substantial. According to the determination of the grey correlation coefficient in *Table 5*, the data in *Table 6* are ranked. Return on assets has the weakest correlation with total profits, while intangible assets have the strongest correlation. The correlation coefficient's top three factors are intangible assets, financial assets, and return on sales. Hence, in the sphere of carbon accounting and green finance, Chinese energy companies have begun to increase their return on sales, return on intangible assets, and return on financial assets. Return on investment of financial instruments is followed by return on equity, total borrowings, inventories, and return on assets.

Table 5. *Correlation coefficient*

Year	Investment income of financial instruments	Financial assets	Inventory	Intangible assets	Total borrowings	ROE	ROA	ROS
2018	0.344	0.990	0.441	0.990	0.561	0.415	0.450	0.334
2019	0.333	0.638	0.333	0.434	0.333	0.333	0.333	1
2020	0.752	0.375	0.851	0.474	0.755	0.752	0.794	0.714
2021	0.740	0.729	0.333	1	0.333	0.571	0.333	0.397

Table 6. *Ranking of grey correlation degrees*

Factors	Correlation degree
Intangible assets	0.725
Financial assets	0.683
ROS	0.611
Investment income of financial instruments	0.542
ROE	0.518
Total borrowing	0.496
Inventory	0.490
ROA	0.478

Comparative benefits of the new and existing models

The new model constructed in this research differs from existing ones in the following aspects: Previous research has developed mathematical formulas for green economic growth in specific fields. The model proposed herein is a systematic diagram derived

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through the combined research method of DEMATEL-ISM-MICMAC-GREY. It more intuitively reflects the internal mechanism of action among various dimensions, distinguishing it from the mathematical formulas of previous researches. While existing models only cover carbon accounting or the significance research between green finance and economic benefits, this model comprehensively incorporates all three into the interpretive structural model from the perspective of interdisciplinary correlation. Previous researches have elaborated on mathematical analyses of green economic growth driven by one or several factors in specific fields, condensing them into universal mathematical laws; in contrast, this research conducts interactive qualitative and quantitative research on the factors involved in existing achievements, verifying the validity of these universal mathematical laws and further extending the practical scope of previous research. Additionally, existing models have taken state-owned enterprises and non-state-owned enterprises as research objects, whereas this research focuses on the top 30 energy companies listed in the *2022 White Paper on the Competitiveness of New Energy Companies*, making the results more representative.

Policy implications

Market and legislation construction

Combining previous research findings with those of this research, policy recommendations on key factors are proposed, with a standardized market system as the foundation. Presently, there are only seven pilot carbon emission trading markets, which encompass trading services, carbon emission quota training, carbon GSP certification for emission reduction, national voluntary emission reduction certification, and ecological compensation certification for voluntary emission reduction. The policy cuts carbon emissions by 280,800 metric tons and reduces carbon emission intensity by 11.59% in the pilot areas (Wu et al., 2024). For companies nationwide, market participation remains low, with most not engaging.

To promote participation of national and global companies in carbon emission trading, specific measures should be implemented. First, market access requirements should be relaxed. Second, supervision should be strengthened. Third, online integrated trading systems should be developed.

Prices for carbon emissions shall vary based on the aggregation of energy-intensive and high-emission companies. Set a maximum or minimum price based on amount fluctuation of transaction to preserve low-emission companies' fundamental emission rights.

China's carbon emission market aims to establish a "1 + 3 + N" legal framework. To date, "1 + 3" has been implemented, notably "Regulations on the Administration of Carbon Emission Trading," "Measures for the Management of Third-party Verification Institutions," and "Measures for the Administration of Market Trading." However, the "N" component—specific regulations—still requires further supplementation. When developing these rules, priority should be given to factors with a high degree of centrality and low causal intensity, which are simultaneously influenced by other factors while significantly impacting the achievement of economic benefits. Additionally, factors with strong dependency and driving degrees must be emphasized. Energy companies with high grey correlation should be prioritized, as these factors represent companies seeking economic benefits through energy conservation and emission reduction.

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Mandatory and voluntary carbon disclosure

Current research indicates that large and medium-sized state-owned enterprises (SOEs) possess more substantial resources and are more inclined to disclose environmental information related to carbon emissions, aiming to build a positive public reputation for attracting investment. By contrast, small and non-state-owned enterprises may violate emission regulations to pursue profits, owing to their limited capabilities and lax management.

Through analyzing the annual reports and social responsibility reports of representative energy companies, this research found that large companies disclosing ample carbon information draw high attention from information users. Thus, implementing voluntary carbon information disclosure is feasible, while compulsory disclosure should be imposed on small companies with a higher propensity to violate regulations. This is consistent with the findings of the existing studies mentioned below. The mandatory nature of government regulation can drive both formal and informal environmental regulations to gradually evolve into crucial forces influencing the regional eco-innovation practices of market entities (Zhao et al., 2023).

Project-based compulsory disclosure places energy-intensive and carbon-emitting projects under supervision within a more open and transparent setting. This measure boosts the incentive for companies to conserve energy and reduce emissions throughout the project implementation process. The implementation of voluntary disclosure of carbon in areas of companies with low carbon emissions adhere to the principle of cost-effectiveness and avoid excessive workload.

Levying carbon taxes for environmental public goods

Companies with excessive carbon emissions must pay a compensate with progressive tax rate for the negative externalities generated by carbon emissions and mitigate the damage to social welfare. The negative externality of carbon emissions results in environmental impacts that transcend territorial and national boundaries. Therefore, revenue from carbon taxes should be allocated to environmental public goods. Increasing the tax burden on companies stimulates the adoption of new production technologies and enhances managerial efficiency. Carbon tax design should also consider revenue sustainability. Within the strategic framework of pollution reduction, the negative impact on China's economy is estimated to remain within 0.2% (Jia and Lin, 2020).

Encouragement of green finance innovation

Finance serves as the primary mechanism for market participants to achieve portfolio investment returns, manage risk minimization, and enhance investment-financing efficiency. To align with the goals of carbon peaking and carbon neutrality, multiple provinces in China have developed diverse financial instruments, including carbon funds, green loans, carbon credit, and carbon emission futures, designed to support companies in achieving low-carbon production. Given the varying stages of regional economic growth and industrial structure diversity, the mix of green financial products requires tailoring to meet the investment-financing needs of new companies in emerging industries and continuously expand market participation. The government should foster a conducive business environment for companies actively engaged in energy conservation and emission reduction initiatives while enhancing support for financial institutions and their green financial product innovations through digital innovation. Given that China's

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relevant policies targeting emission mitigation have been proven to effectively mitigate the emission effect. Such as the carbon emission trading scheme and low-carbon city development pilots (Jiang et al., 2024).

Conclusions

Carbon accounting and green finance are integrated into production and administrative processes, yielding environmental and economic benefits through energy conservation and emission reduction. Therefore, understanding the interrelationships and causal linkages among internal factors of carbon accounting, green finance, and economic benefits is beneficial for companies to optimize funding strategies scientifically. From a policy and legislative perspective, such insights also assist governments in formulating environmentally friendly development strategies.

In light of this, after substantial literature analysis and research, this research identified 23 significant factors across six dimensions. The empirical model research of DEMATEL-ISM-MICMAC-GREY reveals that $S_3, S_4, S_7, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, S_{18}, S_{19}, S_{20}, S_{21}$ are the essential factors of strong centrality and weak causality, respectively. S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{13}, S_{14}, S_{15}, S_{16}, and S_{17} are the factors with the same driving and dependence degree. There are eight aspects that have been implemented by leading energy companies closely tied to important factors. Among them, factors with the first 50% of grey correlation degrees are intangible assets, financial assets, ROS, and investment income on financial instruments.

To enhance the synergy of factors at all levels of the hierarchical structure model and deliver systematic economic benefits, efforts should focus on establishing a standardized foundation within enlightened policy-making frameworks. Based on findings from the DEMATEL-ISM-MICMAC-GREY model, policy recommendations emphasize the establishment of a mandatory and voluntary carbon information disclosure system. Over time, it is essential to cultivate environmental awareness among micro, small, and medium-sized companies (MSMEs) while using the initiatives of large/medium-sized or state-owned enterprises as benchmarks. Emissions exceeding quotas should be subject to a carbon tax, with revenue exclusively allocated to public goods environmental protection.

Additionally, strategies should promote green financial product innovation to provide preferential funding for corporate energy conservation and emission reduction projects. Support should also be extended to assist financial institutions in managing green digital transformation and reducing energy consumption.

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APPENDIX

Data source

The research objects, energy companies, are selected from the Chinese energy companies listed in the *2022 White Paper on the Competitiveness of New Energy Companies*. The financial data of each company is derived from the annual reports disclosed on the companies' official website or the annual financial reports released on http://www.cninfo.com.cn/new/index.

Table A1. *Direct-influence matrix A of factors*

S_i	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}	S_{19}	S_{20}	S_{21}	S_{22}
S_1	1	1	2.54	2.54	2.15	3.46	4	1.62	3.38	4	3.54	2.77	3.31	4	2.23	3.54	1.31	1.69	1.85	3.69	3.23	2.38
S_2	1.08	1	3	2.77	1.77	1.62	3.38	2.54	3	4	2.77	3.08	3.15	1.46	1.77	3.62	2.54	2.62	2.62	3.23	2.85	2.38
S_3	3.08	2.92	1	3.46	2.77	3.15	2.92	1.46	2	3.46	3.62	2.85	3.23	1.92	2.46	2.69	3.23	3.31	2.92	3.15	3.23	2.15
S_4	3.23	2.54	3	1	2.46	2.46	3.46	2.31	3.08	3.38	3.46	2.85	3.31	3.15	3.69	3.23	2.46	2.23	2.77	3.62	1.77	3.08
S_5	2.69	2.77	2.77	3.15	1	3.31	4	2.62	3.23	3.46	3.62	2.23	3.62	2.54	1.31	1.69	1.54	3.08	2.15	2.92	3.38	3.38
S_6	3.23	3.15	3.00	3.54	3	1	3.46	3.54	4	3	2.92	3	3.31	1.15	1.08	1.62	1.15	1	1.23	2.77	3.62	3.23
S_7	1.23	1.23	1.85	2.31	1.54	2.77	1	2.23	3.54	3.54	3.69	2.92	2.38	1.46	1.85	2.77	2.62	2.62	2.46	3.46	2.08	2.85
S_8	2.77	3.23	2.08	2.31	1.15	1.38	1.62	1	1.77	1.85	2.46	1.92	1.46	1.54	1	2.38	1.85	2.69	1.46	2	1.85	1.38
S_9	1.23	2.15	2.54	1.77	2.54	2.77	2.15	1.69	1	2.85	1.38	2.46	2.15	3.15	2.85	3.54	3.23	3.54	3.15	3.69	3.46	2.38
S_{10}	2.92	2.08	2.77	3.46	2.38	3.62	3.08	3.31	2.62	1	3.46	2.77	3.77	1.31	3.54	3.77	2.08	3	2.85	3.54	3.38	2.62
S_{11}	2.23	1.38	2.77	3.31	1.77	2.54	3.23	2.38	1.85	3.31	1	2.54	2.46	1.69	2	3	1.85	1.31	2.46	2.31	3.15	3.38
S_{12}	1.31	1.31	2.62	1.38	1.85	1.85	3.23	1.62	2.77	3	3.23	1	3	3.31	1.38	3.62	2.69	2.46	3.15	1.69	2.31	2.62
S_{13}	3.62	2.69	3.15	3.15	2.15	2.62	2.92	2.62	2.85	2.92	3.46	3.23	1	2.77	3.15	3	3.38	2.54	2.77	3.08	3.08	3.31
S_{14}	3.23	1.15	1.15	1.31	1.08	1.15	3.08	1.31	1.85	1.15	1.62	1.23	1.31	1	1.15	1.23	1.15	1	1.08	2.38	1	1.38
S_{15}	1.62	1.31	1.38	1.38	1.54	2.08	2.54	2.08	3.08	3.69	3.08	2.92	2.92	2.92	1	1.92	2.31	1.77	2.77	2.31	2.38	1.38
S_{16}	2.92	3.23	4.00	3.38	1.31	2.62	2.62	1.85	2.38	2.31	3	3.31	3.15	1.54	2.23	1	1.62	1.62	1.54	3.62	2.46	2.08
S_{17}	1.54	1.69	2.85	1.85	1.69	2.23	2.77	2.23	2.92	3.31	3.54	2.54	2.85	2.23	2.15	2.69	1	2.31	3.69	3.23	2.23	2.54
S_{18}	1.62	2	3.38	2.85	1.31	2.77	3.00	2.54	2.62	2.62	3.23	2.54	3	1.23	2.77	3.31	2.69	1	2.31	2.54	2.15	3.23
S_{19}	2.15	2.92	3.00	2.92	2.54	2.23	3.23	2.54	1.92	3.54	2.77	1.54	2.62	3.31	2.31	3.31	1.92	2.54	1	3.15	2.77	3.08
S_{20}	3.08	2.77	3.23	2.92	2.31	2.46	3.62	3.23	3.38	3.38	3	2.54	2.23	3.69	2.54	3	3.08	2.77	2.38	1	3	3.46
S_{21}	3.69	2.62	2.69	2.85	3	2.77	3.54	2.31	3.54	3	3.08	3.38	3.23	3.62	3.31	3.15	3.23	3.08	3.38	3.08	1	3.23
S_{22}	1.23	2.38	1.62	2.08	1.77	1.23	3.15	1.46	3.15	3.38	3.38	1.69	2.54	1.23	3.15	2.69	2.00	2.38	2.46	3.23	3.15	1

Table A2. *Comprehensive-influence matrix K*

S_i	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}	S_{19}	S_{20}	S_{21}	S_{22}
S_1	0.20	0.19	0.24	0.24	0.19	0.24	0.29	0.20	0.26	0.29	0.29	0.24	0.26	0.24	0.21	0.27	0.20	0.21	0.22	0.28	0.25	0.24
S_2	0.19	0.18	0.24	0.23	0.18	0.21	0.27	0.21	0.25	0.29	0.27	0.24	0.25	0.19	0.20	0.26	0.21	0.21	0.22	0.27	0.24	0.23
S_3	0.24	0.22	0.23	0.26	0.20	0.24	0.29	0.21	0.25	0.30	0.30	0.25	0.27	0.22	0.22	0.27	0.23	0.24	0.24	0.29	0.26	0.25
S_4	0.24	0.22	0.26	0.23	0.20	0.23	0.30	0.22	0.27	0.30	0.30	0.25	0.27	0.24	0.24	0.28	0.22	0.22	0.24	0.29	0.24	0.26
S_5	0.23	0.22	0.25	0.25	0.18	0.24	0.30	0.22	0.27	0.29	0.29	0.24	0.27	0.22	0.20	0.25	0.21	0.23	0.23	0.28	0.26	0.26
S_6	0.23	0.21	0.24	0.25	0.20	0.20	0.28	0.22	0.27	0.28	0.27	0.24	0.26	0.19	0.19	0.24	0.19	0.19	0.20	0.26	0.26	0.25
S_7	0.18	0.17	0.21	0.21	0.16	0.21	0.22	0.19	0.24	0.26	0.26	0.22	0.23	0.18	0.19	0.24	0.20	0.20	0.21	0.25	0.22	0.22
S_8	0.17	0.17	0.17	0.18	0.13	0.15	0.19	0.14	0.18	0.19	0.20	0.17	0.17	0.15	0.14	0.19	0.15	0.17	0.15	0.19	0.17	0.16
S_9	0.19	0.19	0.23	0.22	0.18	0.22	0.25	0.19	0.22	0.26	0.24	0.22	0.23	0.22	0.21	0.26	0.22	0.22	0.22	0.27	0.25	0.23
S_{10}	0.24	0.22	0.26	0.27	0.20	0.26	0.30	0.24	0.27	0.27	0.30	0.26	0.29	0.21	0.24	0.29	0.22	0.24	0.25	0.30	0.27	0.26
S_{11}	0.20	0.17	0.22	0.23	0.17	0.20	0.26	0.19	0.22	0.26	0.22	0.21	0.23	0.18	0.19	0.24	0.19	0.18	0.20	0.24	0.23	0.23
S_{12}	0.18	0.17	0.21	0.19	0.16	0.19	0.25	0.17	0.23	0.25	0.25	0.19	0.23	0.20	0.18	0.24	0.19	0.19	0.21	0.22	0.21	0.22

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S_{13}	0.25	0.22	0.26	0.26	0.20	0.24	0.29	0.23	0.27	0.30	0.30	0.26	0.24	0.23	0.24	0.28	0.24	0.23	0.24	0.29	0.27	0.27
S_{14}	0.15	0.11	0.13	0.13	0.10	0.12	0.17	0.11	0.14	0.15	0.15	0.13	0.14	0.11	0.11	0.14	0.11	0.11	0.12	0.16	0.13	0.13
S_{15}	0.17	0.16	0.19	0.18	0.15	0.18	0.23	0.17	0.22	0.25	0.24	0.21	0.22	0.19	0.16	0.21	0.18	0.17	0.20	0.22	0.20	0.19
S_{16}	0.21	0.20	0.25	0.24	0.16	0.21	0.26	0.19	0.23	0.25	0.26	0.23	0.24	0.19	0.20	0.22	0.19	0.19	0.20	0.26	0.23	0.22
S_{17}	0.19	0.18	0.23	0.21	0.17	0.21	0.26	0.19	0.24	0.26	0.27	0.22	0.24	0.20	0.20	0.24	0.18	0.20	0.23	0.26	0.22	0.22
S_{18}	0.19	0.19	0.24	0.23	0.16	0.22	0.26	0.20	0.24	0.26	0.26	0.22	0.24	0.19	0.21	0.25	0.21	0.18	0.21	0.25	0.22	0.24
S_{19}	0.21	0.21	0.24	0.24	0.19	0.22	0.28	0.21	0.24	0.28	0.27	0.22	0.25	0.22	0.21	0.26	0.20	0.21	0.20	0.27	0.24	0.24
S_{20}	0.24	0.22	0.26	0.25	0.20	0.24	0.30	0.23	0.28	0.30	0.29	0.25	0.26	0.24	0.23	0.28	0.23	0.23	0.24	0.26	0.26	0.27
S_{21}	0.26	0.23	0.27	0.27	0.22	0.25	0.32	0.23	0.29	0.31	0.31	0.27	0.29	0.26	0.25	0.29	0.25	0.25	0.26	0.30	0.25	0.28
S_{22}	0.18	0.18	0.20	0.20	0.16	0.18	0.25	0.17	0.23	0.25	0.25	0.20	0.22	0.17	0.20	0.23	0.18	0.19	0.20	0.25	0.23	0.19

Table A3. *Reachability matrix M*

S_i	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}	S_{19}	S_{20}	S_{21}	S_{22}	S_{23}
S_1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_2	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_3	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_4	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_6	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_7	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_8	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_9	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{10}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{11}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{12}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{13}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{14}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{15}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{16}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{17}	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S_{18}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
S_{19}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
S_{20}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
S_{21}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
S_{22}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
S_{23}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

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Table A4. *Influence factors of reachability matrix*

S_i	Reachability set $R(S_i)$	Antecedent set $A(S_i)$	Intersection set $C(S_i)$	Beginning $B(S_i)$	Ending $E(S_i)$
S_1	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_2	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_3	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_4	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_5	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	5	5	5	
S_6	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_7	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_8	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_9	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{10}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{11}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{12}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{13}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{14}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{15}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{16}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{17}	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17		
S_{18}	18,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,21,22	18,22		
S_{19}	19,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,19	19		
S_{20}	20,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,20	20		
S_{21}	18,21,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,21	21		
S_{22}	18,22,23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,21,22	18,22		
S_{23}	23	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23	23		23

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***Table A5.** Dependence and driving degree of factors*

S_i	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}	S_{19}	S_{20}	S_{21}	S_{22}	S_{23}
Dependence degree	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	3	2	2	4	3	1
Driving degree	17	17	17	17	1	17	17	17	17	17	17	17	17	17	17	17	17	20	18	18	18	20	23

***Table A6.** Nomenclature*

Abbreviations/ variables	Explanations	Abbreviations/ variables	Explanations
DEMATEL	Decision-making trial and evaluation laboratory	$x_1(k)$	Comparative series of factor 1
ISM	Interpretive structural model	$x_2(k)$	Comparative series of factor 2
MICMAC	Matrice d'Impacts croisés multiplication appliquée à un classement	$x_m(k)$	Comparative series of factor m
GREY	Grey correlation analysis	$y_0(k)$	Dimensionless parent series
GCG	Green credit guidance	$y_i(k)$	Comparative series
GCP	Green credit policy	$\Delta_i(k)$	difference series
MVA	Market value of accounting based	$\xi_i(k)$	Correlation coefficient between the indicator K of sample i and the optimal indicator
ROA	Return on assets	ρ	The discriminate coefficient that used to weaken the overvalued distortion of $maxmax\,\Delta\, i(k)$
ROE	Return on equity	M	Reachable matrix M
ROS	Return on sales	$WACC$	Weighted Average Cost of Capital
Tobin's Q	The ratio of market value to the replacement cost of its assets	S_1	Inventory
CFP	Corporate financial performance	S_2	Intangible assets
A	Initial direct influence matrix	S_3	Financial instruments
a_{ij}	Degree of influence of factor on factor	S_4	Environmental assets
m	Row	S_5	Benchmark
n	Column	s_6	Disclosure policy
i	Number of factor	S_7	Disclosure content
j	Number of factor	S_8	Disclosure mode
F	Normalized direct influence matrix	S_9	Audit and verification
K	Exhaustive influence matrix	S_{10}	Carbon trade
C	The most significant value	S_{11}	Carbon credit loans
r_i	The comprehensive influence degree of this factor on other factors	S_{12}	Carbon bond
c_i	The comprehensive influence degree of this factor caused by other factors	S_{13}	Carbon fund
k_{ij}	Data from comprehensive influence matrix	S_{14}	Carbon trust
B_{ij}	Adjacency matrix	S_{15}	Carbon tax
γ	Experience threshold	S_{16}	Carbon financial products
D	Reachable matrix	S_{17}	Equity assets
I	Identity matrix	S_{18}	WACC
$R(S_i)$	Reachability set	S_{19}	ROE
$A(S_i)$	Antecedent set	S_{20}	ROA
$C(S_i)$	Common set	S_{21}	ROS
$B(S_i)$	Beginning set	S_{22}	Tobin's Q
$E(S_i)$	Ending set	S_{23}	Economic benefits
$x_0(k)$	Parent series		

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