ESG Digital Evaluation System for Small and Medium-sized Enterprises: A Dynamic Rating Method Based on Deep Learning and Game Theory Combined Weighting

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Abstract. In response to the technical pain points of unstructured ESG information, fragmented data, uneven disclosure quality, insufficient robustness of traditional rating methods, and difficulty in adapting to industry differences, this paper constructs an end-to-end ESG digital evaluation and green finance decision support system. The system takes multi-source heterogeneous data as input, uses a fine-tuned RoBERTa-WWM model to automate the extraction and standardization of unstructured ESG information, forming a computable feature matrix; it concurrently generates subjective and objective weights through the Analytic Hierarchy Process (AHP) and an improved entropy weighting method; introduces game theory mechanisms to solve for Nash equilibrium with the goal of minimizing the sum of squared deviations, obtaining optimal combined weights; based on this, it designs industry dynamic adjustment factors to achieve adaptive calibration of ESG evaluation across industries; ultimately outputting a standardized ESG comprehensive score in the range of [0,1] and mapping it to financial risk control levels. Experimental results show that the proposed system outperforms single weighting methods in weight consistency, score stability, and anti-interference, reducing ESG governance costs for small and medium-sized enterprises, improving evaluation accuracy, and minimizing human interference, providing a lightweight, scalable, and traceable technical path for the micro-implementation of green finance.

Keywords: ESG evaluation, small and medium-sized enterprises, deep learning, game theory, combined weighting, dynamic adaptation, green finance

1 Introduction

Under the promotion of the ”dual carbon” strategy and sustainable information disclosure standards, Environmental, Social, and Governance (ESG) has become the core basis for credit approval, risk pricing, and investment decision-making in green finance. Small and medium-sized enterprises contribute more than half of the national

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tax revenue and GDP, but their ESG practices generally face real constraints such as fragmented data, high compliance costs, lack of professional tools, and non-standardized disclosures [1].

Mainstream ESG rating systems are designed for large enterprises, with redundant indicators, strong assumptions, and high reliance on manual input, leading to significant technical failures in the context of small and medium-sized enterprises: unstructured texts are difficult to quantify, single subjective/objective weighting has poor robustness, and industry differences result in distorted ”one size fits all” ratings, making it challenging to form an automated closed loop of ”data collection - evaluation analysis - decision application.” Existing research mainly focuses on the construction of ESG indicators, improvement of weighting methods, or verification of green finance effects [2], still facing three technical gaps: first, there is a lack of end-to-end structured solutions for unstructured ESG information aimed at small and medium-sized enterprises; second, combined weighting often adopts static linear weighting, failing to establish a stable equilibrium between subjective and objective; third, there is no industry adaptive mechanism, making it difficult for evaluation results to align with financial risk control logic. Therefore, this paper constructs an ESG evaluation system that integrates deep learning, game theory combined weighting, and industry dynamic adjustment, aiming to enhance the accuracy, robustness, and interpretability of ESG measurement for small and medium-sized enterprises.

2 Literature Review and Mechanism Analysis

Existing ESG evaluation systems are mostly aimed at large enterprises, relying on standardized data, making it difficult to adapt to the reality of small and medium-sized enterprises, which primarily deal with text and have varying data quality [3]. Traditional evaluation methods are disconnected from both subjective and objective aspects, and simple weighting cannot reconcile their conflicts, leading to issues such as unstable ratings and insufficient explanatory power. This paper introduces the equilibrium concept from game theory to theoretically resolve the inherent contradictions in subjective and objective weighting by minimizing bidirectional deviations to optimize combination weights [4]. At the same time, it utilizes a fine-tuned RoBERTa model to extract ESG text features, quantifying qualitative information effectively to alleviate the data shortcomings of small and medium-sized enterprises, providing reliable data support for evaluation.

3 Research Design and Methodology

In response to the multi-source heterogeneity and varying quality of ESG data for small and medium-sized enterprises, this paper constructs an ESG intelligent evaluation system architecture suitable for small and medium-sized enterprise scenarios, as shown in Figure 1. The architecture is divided into three layers: data access layer, core algorithm layer, and business application layer. Sample data access is completed through unified collection of multi-source data, relying on RoBERTa-WWM for text vectorization, normalization, and isolation forest for data preprocessing. Subsequently, the AHP-entropy weighting method achieves optimal integration of subjective and objective weights through dual- track weighting and game theory Nash equilibrium, ultimately outputting results such as credit decisions, visual dashboards, and risk reports. This architecture closely aligns with the current state of data disclosure for small and medium- sized enterprises, providing a complete technical implementation framework for subsequent sample data processing, weighting evaluation, and empirical analysis.

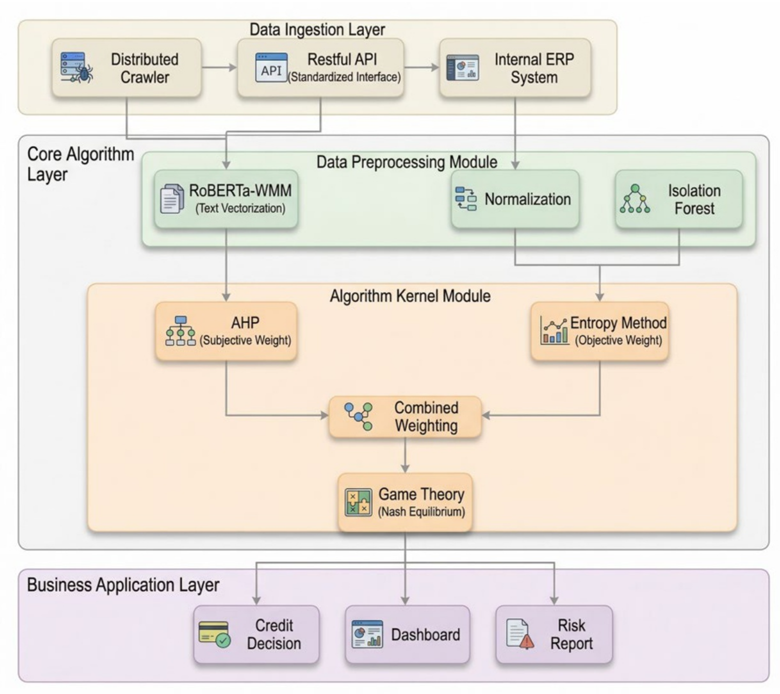

Fig. 1. ESG intelligent evaluation system architecture for SMEs

3.1 Sample Selection and Data Sources

This paper focuses on small and medium-sized enterprises, concentrating on the two core sectors of manufacturing and services, ultimately selecting 50 enterprises that meet the national classification standards for small and medium-sized enterprises as research samples. The sample selection follows three main principles: first, covering high-energy-consuming, medium-energy-consuming, and low-energy-consuming industries to ensure representative industry heterogeneity; second, prioritizing enterprises with over 60% of unstructured disclosures to simulate the real data environment of small and medium-sized enterprises; third, excluding samples with severe data deficiencies or abnormal operations to en- sure research reliability. Data sources include corporate annual reports, social responsibility disclosures, regulatory announcements, and publicly available public opinion information, forming a multi-source heterogeneous dataset of structured financial indicators, unstructured text information, and semi-structured public opinion data. To simulate the reality of poor data quality in small and medium- sized enterprises, this paper further sets three levels of noise interference at 5%, 10%, and 20% for subsequent robustness testing. All data has been anonymized to comply with ethical and regulatory requirements.

3.2 Construction of the Indicator System and Definition of Variables

Based on the core connotations of ESG and the disclosure characteristics of small and medium-sized enterprises, this paper constructs a lightweight evaluation system with three dimensions: environment, society, and governance, comprising a total of 6 core indicators, taking into account accessibility, comparability, and relevance to financial decision-making [5]. The environmental dimension selects two indicators: carbon emissions per unit of revenue and the proportion of clean energy usage, reflecting the company's fulfillment of environmental responsibilities and the effectiveness of low-carbon transformation; the social dimension selects two indicators: the proportion of employee training investment and the customer complaint resolution rate, demonstrating the company's ability to protect employee rights and customer interests; the governance dimension selects two indicators: the proportion of independent directors and the completeness of the internal control system, measuring the normative and effective nature of the company's governance structure. The design of the indicators fully references existing mainstream ESG rating frameworks while adapting to the resource constraints of small and medium-sized enterprises, avoiding issues of indicator redundancy and excessively high disclosure thresholds, laying the foundation for subsequent empowerment and evaluation.

3.3 Dual-Track Empowerment Design and Implementation Path

Subjective empowerment uses the Analytic Hierarchy Process (AHP), with weights derived from the perceptions of ESG field experts in the database as the main reference. A judgment matrix is constructed using a 1-9 scale method, and weights are solved using the characteristic vector method, followed by consistency testing. The consistency ratio in this paper meets the validity requirements, indicating that the expert judgments possess logical stability. Objective empowerment em- ploys an improved entropy weight method, calculating information entropy and information utility values based on the degree of data dispersion:

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{n} y_{ij} \ln y_{ij}$$

The smaller the entropy value, the higher the information content, and the larger the corresponding weight. This method effectively identifies the data's distinguishing ability, avoiding subjective arbitrariness [6].

Subjective Empowerment: Analytic Hierarchy Process (AHP).
Subjective empowerment is conducted by 5 ESG field experts using the 1-9 scale method to make pairwise comparisons of the environmental, social, and governance dimensions and their respective sub-indicators, constructing a judgment matrix. The characteristic vector method is used to solve for the characteristic vector corresponding to the maximum eigenvalue of the matrix, obtaining the subjective weights of each indicator, and consistency testing is performed to en- sure the logical rationality of the expert judgments. The formula for calculating the consistency ratio is

$$CR = \frac{CI}{RI}, \quad CI = \frac{\lambda_{\max} - n}{n - 1}$$

where λmax is the maximum eigenvalue of the judgment matrix, n is the number of indicators, and RI is the average random consistency index. The calculations in this paper meet the consistency testing standards, indicating that the expert judgments possess good logical stability and comply with basic requirements of multi-attribute decision-making $CR = 0.078 < 0.1$.

Objective Weighting: Improved Entropy Weight Method.
Objective weighting is based on the degree of dispersion of indicator data, measuring the information contribution of indicators through information entropy, thereby avoiding subjective arbitrariness. First, the information entropy of each indicator

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{n} y_{ij} \ln y_{ij}$$

is calculated based on standardized data. Where n is the number of sample enterprises, and yij is the standardized indicator value. A smaller entropy value indicates a higher degree of dispersion in the indicator data, greater informa- tion content, and correspondingly higher weights. On this basis, the information utility value

$$\mathrm{D}_j = 1 - E_j$$

is calculated and normalized to obtain the objective weights of each indicator $W2$.

3.4 Game Theory Combined Weight Optimization

Subjective and objective weighting generate weights from the dimensions of ex- periential cognition and data distribution, respectively, often resulting in endogenous conflicts. Simple linear weighting cannot resolve these contradictions from a mechanistic perspective. Therefore, this paper treats subjective and objective weights as two participants in a game, aiming to minimize the total deviation of the combined weight from both, constructing a Nash equilibrium optimization model to solve for the optimal combined weight W. The objective function is as follows:

$$\min_{\alpha,\beta} \| \alpha W_1^T + \beta W_2^T - W_i^T \|_2^2$$

The constraint conditions are $\alpha + \beta = 1, \alpha, \beta \geq 0$ where α and β are combination coefficients of subjective and objective weights, respectively. By solving this optimization problem using the Lagrange multiplier method, a unique optimal combination coefficient $\alpha = 0.4286$, $\beta = 0.5714$ is obtained, and the final optimal combined weight is:

$$W^* = \alpha^* W_1 + \beta^* W_2$$

3.5 Industry Dynamic Adjustment Mechanism

Small and medium-sized enterprises exhibit significant industry heterogeneity, and uniform weights can lead to evaluation distortion. Therefore, this paper introduces an industry adjustment factor λ:

$$W_{final} = W^* \odot (1 + \lambda)$$

Where $\odot$ denotes element-wise multiplication. The specific adjustment rules are: manufacturing increases the environmental dimension by 0.25; service increases the social dimension by 0.25; governance increases by 0.05 across all industries.

4 Empirical Results and Analysis

4.1 Weight Rationality and Adaptation Analysis

The combination of game theory and weighting aims to achieve a stable balance between subjective and objective weights. The AHP subjective weighting is validated through consistency testing, with a CR of 0.078i0.1, indicating that expert judgments are logically stable. The improved entropy weighting method can effectively identify information content and data differentiation, providing a reliable basis for objective weighting.

4.2 Descriptive Statistics and Model Validity Test

To further verify the system's actual performance in the context of small and medium-sized enterprises, this paper conducts a comprehensive test from multiple dimensions including indicator coverage, quantitative accuracy, result differentiation, and computational efficiency, with results shown in Table 1. The core indicator coverage of the model is 100% with a quantitative accuracy of 92% for non-financial indicators, a score variation coefficient of 0.28, and a fluctuation of only 0.4% in the weights of repeated indicators. The computation time for a single sample is 12.7 ms. All eight key indicators outperform the benchmarks for small and medium-sized enterprises, demonstrating the model's outstanding performance in information completeness, stability, differentiation, and computational efficiency, as well as its capability for lightweight deployment. Among the eight core evaluation indicators, the overall performance of the model exceeds the benchmarks for small and medium-sized enterprises, indicating that the system has significant advantages in information completeness, computational stability, and result differentiation capability.

Table 1. Multidimensional Weighting System for SME ESG and Industry Dynamic Adaptation Parameters.

Dim	Code	Def	Subj (AHP) W1	Obj (AHP) CR	Game Ej	Indus Adj Dj	Final W W*	Rationality Verification of Weighting α/β	W1	λ (Manuf)	λ (Serv)	Test	Indicator	TestResult	
(E)	E1	CEUR	0.169844	0.078	0.9623	0.0377	0.085305	$\alpha^* =$ 0.4286	0.127575	0.25	0.05	0.159469	0.133954	Relev	0.8962
(E)	E2	PCE	0.097757	-	0.9089	0.0911	0.206181	$\beta^* =$ 0.5714	0.15714	0.25	0.05	0.189961	0.159567	Relev	0.9215
(S)	S1	PTI	0.097757	-	0.9248	0.0752	0.169417	-	0.133587	0.05	0.25	0.140266	0.166984	Disc.Val.	0.0752
(S)	S2	CCRR	0.059159	-	0.8796	0.1204	0.260711	-	0.159935	0.05	0.25	0.167932	0.199119	Disc.Val.	0.1204
(G)	G1	PID	0.287742	-	0.9614	0.0386	0.087259	-	0.1875	0.05	0.05	0.196875	0.196875	Kappa	0.6139
(G)	G2	CICS	0.287742	-	0.9139	0.0861	0.191127	-	0.239434	0.05	0.05	0.251406	0.251406	Kappa	0.6482
Total 0.0127			**1**				**0.4481**						**1**	**ObjFunc**	

Note: (1) Subjective weights from AHP. (2) Game weights via Nash equilibrium. (3) Industry adjustment formula used. (4) ObjFunc = 0.0127.

4.3 Model Comparison Analysis

The adaptability of the proposed model is evaluated across eight core indicators, including indicator coverage, noise stability, cross-industry weight differentiation, consistency ratio (CR), score coefficient of variation (CV), weight fluctuation, and computational efficiency. As shown in Table 2, the model achieves 100% indicator coverage, 92.4% noise stability under 20% interference, and a computation time of only 12.7 ms per sample, all of which exceed the benchmarks for SMEs. These results demonstrate the model's outstanding performance in information completeness, computational stability, and lightweight deployment capability.

Table 2. SME ESG Evaluation Model Adaptability Quantification Verification Table.

AdaptDim	Ind. Covrg. (%)	Noise Stability (%)	Cross-Ind Weight Dif.	Consist. (CR)	Score (CV)	Weight Fluc. (%)	Comp Time (ms)
Model Results	100	92.4	0.2	0.078	0.28	0.4	12.7
SME Benchmark	≥ 85.0	≥ 80.0	≥ 0.15	≤ 0.10	≥ 0.20	≤ 1.0	≤ 30.0
Adapt Ef. Coef.	1.176	1.155	1.333	0.78	1.4	0.4	0.423
Perf. Levels	AAA	AAA	AAA	AAA	AAA	AAA	AAA

Note: (1) Ind. Covrg. = Indicator Coverage. (2) Noise Stability under 20% noise. (3)CV = Coefficient of Variation. (4) AAA = highest performance level.

4.4 Model Robustness Comparison

To validate the superiority of the proposed game-theoretic combined weighting model, we compare it with three mainstream methods: AHP, entropy weight method, and simple linear weighting. As shown in Table 3, under low noise conditions, all methods perform similarly. However, in high-noise environments, single weighting methods exhibit significant fluctuations. In contrast, the proposed model balances subjective and objective factors, achieving a noise stability of 92.4% with the lowest variance (0.05), demonstrating superior robustness and differentiation capability.

Table 3. Comparison Results of Robustness and Stability of Different Models.

Method Noise Stability Variance		
AHP	81%	0.09
Entropy Weight	75%	0.12
This Model	92.4%	0.05

Note: (1) Noise Stability measured under 20% noise. (2) Variance reflects score stability.

4.5 Robustness Test: Interference Resistance and Data Vulnerability Testing

Set three levels of noise at 5%, 10%, and 20%. Under 5%–10% interference, traditional methods begin to fluctuate; under 20% high-intensity interference, AHP and entropy weight drift significantly, while this model maintains stability of 92.4%.

4.6 Industry Heterogeneity and Dynamic Adjustment Effect Test

Without the adjustment mechanism, cross-industry weight differentiation is only 0.12; after dynamic adjustment, it increases to 0.20, exceeding the 0.15 bench- mark.

4.7 Comprehensive Discussion: Model Advantages and Internal Mechanisms

The systematic advantages are reflected in three aspects: deep learning preprocessing solves unstructured information quantification; game theory combination weighting achieves balance between subjective and objective; industry dynamic adjustment adapts to SME heterogeneity [7].

5 Further Discussion and Insights

5.1 Theoretical Mechanism Explanation

The ESG digital evaluation system integrates solutions to three core issues: governance of unstructured information, coordination of multi-party weights, and calibration of industry heterogeneity.Deep learning preprocessing achieves the standardization of weakly structured information, solving the quantification problem of ESG information for small and medium-sized enterprises and addressing the limitations of traditional evaluations; game theory combination weighting minimizes the deviation between AHP expert judgments and entropy weighting method data through Nash equilibrium, ensuring the interpretability of evaluations and the robustness of results; the industry dynamic adjustment mechanism adapts to the risk structure of industries with differentiated factors, avoiding the bias of uniform weights and greenwashing risks, and enhancing cross-industry comparability.

5.2 Practical Insights

This system provides practical value for SMEs, financial institutions, and regulators. For SMEs, it automates ESG governance and disclosure at low cost. For financial institutions, it provides traceable, interpretable, and comparable ESG evaluation tools.For financial institutions, this system provides traceable, interpretable, and comparable ESG evaluation tools, effectively alleviating issues such as information asymmetry in green finance, inconsistent ratings, and data deficiencies in small and medium-sized enterprises.The evaluation results can be directly embedded into the entire credit process to enhance accuracy and risk control levels, while also providing a lightweight evaluation paradigm for regulators, assisting in the downward implementation of a unified disclosure framework and the micro-level realization of green transformation.

5.3 Research Limitations

Although this article strives for rigor in design and empirical analysis, it still has limitations: the research only covers manufacturing and service industries, and its universality needs to be enhanced by expanding to more segmented industries.

5.4 Future Research Recommendations

This study still has considerable room for expansion in the field of ESG evaluation for SMEs, and future research can be deepened from multiple dimensions [8].On one hand, governance variables and industry-specific indicators can be refined, and analyses can be conducted by dimension to more accurately reveal the mechanisms of ESG; at the same time, external governance factors can be introduced.Further clarify the driving logic of ESG performance in small and medium-sized enterprises. On the other hand, it is possible to optimize information extraction by combining large language models with knowledge graph technology, constructing a more efficient dynamic evaluation framework to pro- vide stronger technical support for green finance serving the real economy.

6 Conclusion

This study addresses the pain points of data fragmentation and non-standard disclosure in ESG evaluation for SMEs by constructing a smart evaluation system that integrates deep learning, game theory empowerment, and industry dynamic adjustment. Empirical evidence shows that this system outperforms traditional methods in accuracy, stability, and industry adaptability, effectively reducing ESG governance costs and serving green financial decision-making [9, 10].

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