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Research on the Construction of a Financial Crisis Early Warning Model for Listed Companies from the Perspective of ESG: Taking the Lithium Battery Industry as an Example

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Abstract

Traditional financial crisis early warning models for listed companies rely predominantly on conventional financial indicators and often overlook ESG risk and its impact on corporate performance. This limitation becomes particularly evident in policy- and regulation-intensive industries such as lithium battery manufacturing, where existing models demonstrate insufficient accuracy. Our study develops a novel dynamic financial crisis early warning model that incorporates ESG factors to increase both precision and predictive power. Using 66 representative lithium battery companies from China's securities market as research subjects, we select 21 financial metrics across six dimensions: debt repayment capacity, operational efficiency, growth potential, cash flow generation, and ESG performance. Through KMO test validation, 19 indicators were identified as model factors for entropy-weighted logit regression analysis. The findings reveal a significant negative correlation between ESG performance and financial risk. Validation through 30 randomly selected companies with similar ESG ratings demonstrates the model's reliability, providing actionable insights for lithium battery industry risk management. This research explores theoretical and practical pathways for integrating ESG principles into financial crisis early warning systems, establishing a composite model that combines traditional financial signals with nonfinancial ESG indicators. The proposed framework offers investors, regulators, and corporate managers more forward-looking and comprehensive decision-making support.

Keywords

financial crisis early warning, lithium battery industry, entropy weighting method-logit regression

1. Introduction

1.1 Research Background

Driven by the deepening of global sustainable development strategies and increasingly stringent capital market regulations, corporate environmental, social, and governance (ESG) performance has become a critical factor influencing financial risk early warning systems. This study focuses on constructing a financial crisis early warning model for listed companies in the lithium battery industry from an ESG perspective. Data from the East Money Choice Financial Terminal show that as of August 2025, 173 companies with special treatment

(ST) or *ST status already exist in China's A-share market. Therefore, establishing a scientific, efficient, and forward-looking financial crisis early warning system has become an urgent requirement to maintain the healthy development of capital markets (Altman, 1968).

Traditional financial early-warning models have evolved from initial single-variable frameworks to statistical tools such as multivariate linear discriminant analysis and logistic regression and then to machine learning approaches such as support vector machines (SVMs) and neural networks in recent years. However, these models share common limitations: first, the lagging and partial nature of indicator systems. Most models rely heavily on historical financial statement data publicly disclosed by companies, which inherently lag in timeliness and fail to fully reflect a company's true value. Second, the absence of information dimensions. Traditional models neglect nonfinancial information crucial for long-term corporate development, particularly the environmental, social, and governance (ESG) factors, which have gained global prominence in recent years (Ohlson, 1980).

A growing body of empirical research demonstrates that strong ESG performance enables enterprises to achieve lower financing costs, enhance brand reputation, and strengthen risk resiliency. However, while the importance of ESEs has reached a consensus, their effective and quantifiable integration into financial crisis early warning models remains an urgent academic frontier requiring exploration. This study innovatively employs the entropy weighting method with logit regression, utilizing China's mainstream ESG rating systems as data sources. The primary data channels include the following: 1. Dongcai Choice Financial Terminal Database: As a leading domestic financial data provider, this database offers all required financial metrics, including balance sheets, income statements, and cash flow statements. 2. Corporate annual reports and social responsibility reports: Direct access to official announcements and annual filings from listed companies. 3. Third-party ESG rating agencies, Institutions such as Shangdao Ronglv and China Securities Index Co., Ltd., provide crucial input variables through their ESG ratings and scoring data, but we still focus primarily on the Huazheng ESG rating as our main export (Friede et al., 2015).

1.2 Research Significance

1.2.1 Theoretical Implications

This study enriches and expands financial crisis early warning theories by breaking down barriers between traditional financial data and ESG nonfinancial metrics, establishing a multilevel, multidimensional framework. Specifically, we employ the entropy weighted logit model (EWLogit), a statistical method that objectively assigns weights and handles nonlinear relationships through linear regression. We anticipate that ESG composite scores will serve as key predictors when integrated into the classic logit model. Through empirical analysis of A-share listed companies in the lithium battery industry on the Shanghai and Shenzhen stock exchanges, we aim to verify whether ESG information has significant predictive power. Furthermore, this research explores effective measurement and quantification methods for ESG performance, which is crucial for advancing ESG principles in investment and risk management practices.

In the selection of indicators, this study innovatively introduces the "intangible assets/total assets" ratio (intangible asset proportion) to better assess technology-intensive enterprises such as lithium battery manufacturers in the knowledge economy era. Through principal component factor analysis (PCF), we screened and reduced the dimensions of the core indicators, selecting 19 financial metrics from six aspects: debt repayment capacity, operational efficiency, growth potential, cash flow generation, corporate governance, and ESG (social, ethical, and governance) indicators for factor analysis. Furthermore, both the innovative indicators and ESG metrics will undergo independent validation.

1.2.2 Practical Significance

From the perspective of investor protection, the model developed in this study, particularly its quantitative assessment of ESG risk, enables investors to identify potential risks in listed companies more comprehensively and profoundly. When making investment decisions, investors can transcend traditional financial analysis by incorporating ESG performance as a critical risk screening criterion. This approach effectively helps avoid "black swan" events and safeguards investment security.

For listed companies, particularly lithium battery manufacturers, this model enables them to assess their financial health and ESG risk regularly, allowing timely identification of potential financial vulnerabilities. By integrating ESG principles into corporate strategies and daily operations, businesses can enhance governance standards, thereby strengthening core competitiveness and long-term sustainable development capabilities.

For regulatory bodies, early warning models serve as a vital component of corporate oversight, enabling the dynamic monitoring of capital market risk. By identifying high-risk companies early and prioritizing their attention, regulators can proactively implement supervisory measures. This approach helps prevent the transmission of individual risk into systemic risk, thereby safeguarding the fair, just, and stable operation of capital markets.

2. Review of the Literature

2.1 Research on the Financial Crisis Early Warning Model

The core of financial crisis early warning research is to predict the possibility of a company's future financial distress by modeling and using its public information. The evolution of the model can be roughly divided into three stages:

The first stage involves single-variable discriminant models. Early research focused primarily on identifying individual financial ratios that could effectively distinguish between distressed and healthy enterprises (Beaver, 1966), a pioneer in this field, conducted a comparative analysis of 30 financial ratios over the five-year prebankruptcy period between bankrupt companies and normal enterprises, revealing that indicators such as cash flow to total liabilities demonstrated significant predictive power. However, these single-variable models are overly simplistic, overlooking interactions between indicators and resulting in limited prediction accuracy.

The second phase marked the development of multivariate statistical models. Guided by Altman's (1968) Z score model, research entered the era of multivariate (MDA). This model calculates a comprehensive discriminant score through linear combinations of five core financial ratios, significantly improving prediction accuracy (Kim et al., 2013). Ohlson (1993))Ohlson (1993) subsequently introduced logistic regression into this field. Overcoming MDA's restrictive assumptions, such as normal distribution requirements, this model provides interpretable outputs indicating corporate crisis probabilities, thus becoming one of the most classic and widely adopted benchmark models in subsequent studies.

The third stage involves artificial intelligence and machine learning models. With advancements in computer technology, nonparametric and nonlinear machine learning algorithms have been widely applied in financial early warning systems. Neural networks—particularly backpropagation (BP) neural networks—have demonstrated exceptional performance in processing complex financial data because of their robust nonlinear fitting capabilities and self-learning abilities (Tam and Kiang, 1992). The support vector machine (SVM), proposed by Vapnik et al., excels at handling small-sample, high-dimensional problems by identifying optimal classification hyperplanes (Huang et al., 2007). In recent years, ensemble learning approaches such as random forest have gained prominence. By constructing multiple decision trees and aggregating their predictions, the random forest effectively reduces overfitting risks associated with single decision trees while enhancing model stability and accuracy (Breiman, 2001). Some studies have begun exploring hybrid or ensemble models that combine different individual models, such as the stacking framework, with the aim of leveraging the strengths of each individual model for improved predictive performance. However, these approaches remain underutilized in financial early warning applications (Woznicki and Karpio, 2022).

2.2 Research on the Financial Early Warning Index System

The indicator system is the cornerstone of the early warning model, and its scientificity directly determines the success or failure of the model. The indicators in traditional research mainly come from financial statements, which are usually constructed around dimensions:

The key financial indicators include solvency, profitability, operational efficiency, growth potential, and cash flow. However, as economic structures evolve, researchers have increasingly recognized the limitations of purely financial metrics. Some studies have begun incorporating nonfinancial indicators into models, such as corporate governance structures (e.g., equity concentration and board independence), audit opinion types, and executive changes, which have been proven to positively contribute to early warning systems. However, these nonfinancial indicators are often selected in a fragmented manner and lack a systematic theoretical framework (Deakin, 1976).

This study introduces two major innovations rooted in a critical inheritance of existing indicator systems. First, for technology-intensive industries such as lithium battery manufacturing, their core value lies in R&D and technological innovation, which primarily manifests as intangible assets. Overly high or structurally inefficient intangible assets may harbor significant impairment risks, yet existing research rarely examines them as key early warning indicators. Second, the emergence of the systematic nonfinancial information framework ESG provides possibilities for building a more comprehensive indicator system (Lev and Zarowin, 1999).

2.3 Research on the Relationship between ESG Performance and Corporate Financial Risk

The relationships between ESG performance and corporate financial performance and risk have been the focus of academic and practical circles in recent years. Many studies have confirmed the positive impact of ESG performance on corporate value from different perspectives (Barboza et al., 2017).

From the perspective of financing costs, strong ESG performance can send positive signals to capital markets about a company's stable operations and long-term commitment, helping reduce information asymmetry and thereby securing lower equity and debt financing costs. Conversely, companies with poor ESG performance may face higher financing thresholds and costs (Eccles et al., 2014, El Ghoul et al., 2011).

From the perspectives of operational performance and corporate value, exemplary ESG practices (such as energy conservation, employee care, and effective governance) can enhance productivity, stimulate innovation among employees, and strengthen brand reputation. These benefits ultimately translate into higher profitability and market valuation. For example, studies have shown that each additional ESG rating significantly increases a company's Tobin's Q ratio (Orlitzky et al., 2003, Khan et al., 2016).

From a risk management perspective, ESG performance constitutes a vital component of corporate risk governance. Environmental risks (including fines for environmental violations and climate transition challenges), social risks (such as product safety incidents and labor disputes), and governance risks (such as managerial corruption and inadequate internal controls) all serve as potential triggers for financial crises. Through proactive ESG management, companies can effectively identify, mitigate, and avoid these risks, thereby strengthening their operational resilience (Grewal et al., 2021).

While the positive role of ESG performance is widely recognized in academic research, practical implementation still faces challenges. The most significant challenge lies in the diversity of ESG rating systems. Major differences exist among rating agencies (such as international institutions such as MSCI and Sustainalytics and domestic agencies such as China Securities Index Co., Ltd. and Shangdao Green Finance) regarding indicator frameworks, weight allocations, data sources, and evaluation methodologies. These discrepancies can lead to vastly different ratings for the same company, posing difficulties for quantitative research. Therefore, it is crucial to select a comprehensive, timely, updated, and authoritative rating system that aligns with Chinese market characteristics (such as the China Securities ESG Rating used in this study) and maintains consistency throughout research(Platt and Platt, 1991, Deakin, 1976, Christensen et al., 2021).

2.4 Research on Expandable Space

2.4.1 Limits of Perspective and Dimension

Most existing research remains confined to frameworks dominated by financial metrics. While nonfinancial information is occasionally referenced, such references tend to be scattered and supplementary. Notably, systematic studies that integrate ESG performance as a core risk factor within a unified framework, combined with traditional financial indicators and innovation metrics, remain relatively rare (Altman and Hotchkiss, 2021).

2.4.2 Optimization Space of Index Selection

Traditional indicator selection methods predominantly rely on correlation analysis and stepwise regression, which are susceptible to subjective influences. The implementation of more objective mathematical approaches, such as the entropy method and factor analysis, for systematic screening and dimensionality reduction can enhance the scientific rigor of the indicator system. Moreover, exploration of innovation indicators specific to particular industries, particularly intangible assets, remains insufficient (Beaver et al., 2005).

2.4.3 Continuous Innovations in Model Methods

Although machine learning models have been widely adopted, most research still focuses on comparing individual models. Advanced ensemble learning methods (such as stacking) that can integrate the strengths of different models to effectively enhance prediction robustness and accuracy remain in their infancy in the exploration of financial crisis early warning systems (Zmijewski, 1984).

In the above context, this study attempts to build a new paradigm of early warning of financial crisis with more explanatory and predictive power by means of index innovation (basic + innovation + ESG), perspective innovation (ESG as the core) and model innovation (entropy weighting method-logit model) and conducts in-depth empirical verification with the lithium battery industry as an example.

3. Model Construction and Research Design

3.1 Sample Selection and Data Sources

This study focuses on A-share listed companies in Shenzhen and Shanghai. To ensure data accuracy and timeliness, the research period covers 2024 annual reports. Annual report data were sourced from the East Money Financial Terminal, whereas Huazheng ESG ratings were obtained from the Wind Database. For missing data points, manual supplementation was performed by reviewing the annual reports of listed companies.

3.2 Definition of Financial Crisis

The academic community has yet to form a fully unified definition of “financial crisis” or “financial distress”. Its manifestations are diverse, ranging from liquidity constraints and sustained losses to debt defaults and, ultimately, even bankruptcy liquidation as a continuous process. To facilitate model construction, this study requires a clear, quantifiable operational definition. Drawing on the practices of China’s securities market and relevant research, we define listed companies meeting any of the following conditions as being in a “financial crisis” (state=1), whereas others are defined as “financially healthy” (state=0):

A: Special treatment (ST or *ST) is a clear warning issued by regulators to listed companies with abnormal financial conditions or other abnormal conditions.

B: Two consecutive years of negative net profit reflect the continuous deterioration of profitability of the company’s main business, which is a significant signal that the financial situation is facing crisis.

For the core research subject, the lithium battery industry, we selected all companies listed on A-shares within the sample period and classified them under the “lithium battery” sector according to the Shenwan industry classification. After excluding B-shares, H-shares, ST/*ST companies, and those with severely missing financial data, we ultimately obtained annual observation values from over 60 companies as a healthy company sample.

3.3 Indicator System Construction

As shown in Table 1, on the basis of the reference literature and considering data availability, this paper constructs a preliminary indicator pool containing 19 candidate indicators from five traditional dimensions, one innovative dimension and one ESG dimension.

Table 1: Nineteen financial indicators and calculation table for primary elections

Debt paying ability	Asset-liability ratio (A) = total liabilities/total assets
	Current ratio (B) = Current assets/Current liabilities
	Quick ratio (C) = (Current assets-Inventory)/Current liabilities
	Cash ratio (D) = (monetary funds + cash equivalents)/current liabilities
Profitability	Net interest rate on sales (E) = Operating profit/Operating income
	Return on equity (F) = Retained earnings/total assets
	Return on total assets (G) = net profit of an enterprise/average total assets
Cash flow indicators	Cash content of main business income (H) = Net cash flow from operating activities/main business income
	Total cash and cash equivalents ratio (I) = Net cash flow from operating activities/total liabilities
	Cash flow from operating activities per share (J) = Net cash flow from operating activities/total shares
Capacity for development	Net asset growth rate (K) = (net assets at the end of the period-net assets at the beginning of the period)/net assets at the beginning of the period
	Net profit growth rate (L) = (net profit of this year-net profit of last year)/net profit of last year
	The growth rate of main business income (M) = (main business income this year-main business income last year)/main business income last year
	Total asset growth rate (N) = (total assets at the end of the period-total assets at the beginning of the period)/total assets at the beginning of the period
Operation capacity	Inventory turnover ratio (O) = Cost of main business/average balance of inventory
	Accounts receivable turnover ratio (P) = main business income/average balance of accounts receivable
	Total asset turnover ratio (Q) = main business income/total assets
Indicators of innovation	The proportion of intangible assets (R) = intangible assets/total assets
ESG metric	Huadong ESG Rating (S)

3.3.1 Index Screening via the Entropy Weighting Method and KMO Principal Component Factor Analysis

The entropy method is used to assign weights to each index in the model. The smaller the information entropy of the index is, the greater the amount of information provided by the index, the greater the degree of variation, and the higher the weight assigned in the comprehensive evaluation.

To eliminate the influence of dimensions, all the indicators are standardized. Different formulas are used for positive and negative indicators. Suppose that there are m samples and n indicators.

forward pointer:

$$X_i'j = (X_ij - min(X_j))/(max(X_j) - min(X_j))$$

Negative indicators:

$$X_i'j = (max(X_j) - X_ij)/(max(X_j) - min(X_j))$$

Overall score:

$$\text{Comprehensive Score} = \sum_{j=1}^{n} w_j X_{ij}'$$

Owing to space constraints, the remaining weighting and screening steps are omitted here. Through the entropy method, we can obtain objective weights for each indicator, eliminate those with excessively low weights, and construct a comprehensive financial performance score via these weights. As shown in Tables 2 and 3, by calculating the information entropy and variance coefficients, the final weights are determined. Factor analysis aims to reduce highly correlated variables into a few common factors, each representing specific aspects of the original variables. Subsequently, applicability tests, including the KMO (kurtosis index) and Bartlett's test of sphericity, are conducted. Typically, a KMO value greater than 0.6 and statistically significant Bartlett test results ($p<0.05$) indicate that the data are suitable for factor analysis.

The following is the result of the statistical analysis by Stata: (Owing to the large amount of data, this study selects only part of the company data for reference.)

Table 2: Entropy value and KMO value of each factor

Factor	Entropy value	KMO price	factor	Entropy value	KMO price
Asset–Liability Ratio	4.898607	0.7354	inventory turnover ratio	0.6108717	0.5002
Current Ratio	1.833658	0.6682	Accounts receivable turnover (excluding notes receivable)	1.569633	0.7079
Quick Ratio	1.733292	0.6095	turnover of current assets	1.124346	0.5994
Interest Multiple	1.400008	0.4861	Compound growth rate of operating revenue	0.4034405	0.61
Cash Ratio	1.576936	0.7189	Forecast the net profit growth rate attributable to the parent company	0.1419769	0.7371
Return on Equity (ROE)	1.119495	0.7299	Year-on-year growth rate of total assets	0.6220491	0.7822
Total Asset Net Interest Rate (ROA)	2.303491	0.7688	Year-on-year growth rate of net assets	0.4737636	0.6533
Ratio of Non-Financing Net Cash Flow to Total Liabilities	1.801856	0.5198	Net cash flow from operating activities/revenue	1.310883	0.6611
Operating Profit / Total Operating Revenue	1.937546	0.7126	Net cash flow from operating activities per share	1.952133	0.5437
Turnover of Total Capital	0.6579244	0.4407	Share of intangible assets	1.643181	0.5329

Table 3: Factor weights

factor	weight	factor	weight
asset-liability ratio	1.0736	inventory turnover ratio	0.2931
current ratio	0.1517	Accounts receivable turnover (excluding notes receivable)	0.1036
quick ratio	0.1334	turnover of current assets	0.0226
Interest multiple	0.0728	Compound growth rate of operating revenue	0.1085
cash ratio	0.1050	Forecast the net profit growth rate attributable to the parent company	0.2078
Return on equity ROE	0.0217	Year-on-year growth rate of total assets	0.0687
Total asset net interest rate ROA	0.2372	Year-on-year growth rate of net assets	0.2682
Ratio of nonfinancing net cash flow to total liabilities	0.1459	Net cash flow from operating activities/revenue	0.0565
Operating profit/total operating revenue	0.1706	Net cash flow from operating activities per share	0.1732
turnover of total capital	0.0622	Share of intangible assets	0.4810

The differentiation index is introduced to screen the high-value variables, and the relevant indicators are screened after the weights of the negative values are shifted. The comprehensive scoring formula is calculated as follows. In this formula, our goal is to calculate four common factors—namely, the debt-servicing capacity factor, profitability factor, growth capacity factor, and intangible asset factor—as well as ESG rating scores as variables. On the basis of the importance of financial indicators, we select the interaction terms of the asset-liability ratio, ROA (return on assets), cash flow ratio, and ESG, integrate them into the calculation formula, and finally obtain the logarithmic value of the comprehensive score.

$$\begin{aligned} &ln(Comprehensive\ Score) \\ &\quad = \alpha_i + \beta_0 + \beta_1 Factor1_{it} + \beta_2 Factor2_{it} + \beta_3 Factor3_{it} + \beta_4 Factor4_{it} + \gamma ESG_{it} \\ &\quad + \delta_1 (ESG_{it} \times Asset - liability\ Ratio_{it}) + \delta_2 (ESG_{it} \times ROA_{it}) \\ &\quad + \delta_3 (ESG_{it} \times Cash\ Flow\ Ratio_{it}) \end{aligned}$$

Through linear regression analysis of composite scores and individual factors on the basis of their weights, we assigned significant weights to factors with greater importance. The results demonstrated that the linear regression model constructed using 66 observed values exhibited outstanding overall fit and explanatory power. The model showed highly significant overall significance (F(21,44)=297.87, Prob> F=0.0000), achieving a coefficient of determination (R^2) of 0.9930 and an adjusted Adj R^2 of 0.9897. This indicates that the model accounts for approximately 99.3% of the variance in the dependent variable Finance_Score, with high fitting precision (root MSE=0.10158).

Through logistic regression analysis combining ESG rating scores with corporate composite scores, the model demonstrated highly significant overall fit. The likelihood ratio chi² test (LR $\chi^2(45) = 245.67$) yielded a P value <0.0001, strongly rejecting the null hypothesis that “all independent variables have coefficients of zero.” This finding indicates that the included independent variables collectively exhibit strong explanatory power for the dependent variable’s classification. The model’s pseudo R^2 reached 0.532, meaning that it accounts for approximately 53.2% of the variance in the dependent variable.

According to the factor loading matrix, we classify 19 indicators into four common factors in Table 4.

Table 4: Each factor composition

factor 1	Solvency factor	Including indicators such as quick ratio
factor 2	Profitability factor	Including return on equity, operating profit margin and other indicators
factor 3	Growth capability factor	Including indicators such as total asset growth rate
factor 4	Intangible assets factor	Including indicators such as intangible assets/total assets

Through factor analysis, we extracted 4 common factors with a cumulative variance contribution rate of 78.42%, and the specific results are shown in Table 5.

Table 5: Factor analysis results

metric	factor 1	factor 2	factor 3	factor 4
quick ratio (C)	0.795	0.092	0.038	0.058
Net cash flow from operating activities/total liabilities (H)	0.742	0.125	0.052	0.026
Return on equity ROE (F)	0.045	0.807	0.027	-0.011
Operating margin (G)	0.068	0.775	0.024	0.013
Total asset growth rate (M)	-0.015	0.027	0.812	0.021
immaterial assets （R）	0.021	0.014	0.011	0.831

3.3.2 Quantitative Treatment of ESG Indicators

The Huade ESG rating system divides a company rating into nine grades: AAA, AA, A, BBB, BB, B, CCC, CC, and C. To include it in the quantitative model, we carry out numerical mapping. The specific mapping rules are as follows:

C -> 1, CC -> 2, CCC -> 3, B -> 4, BB -> 5, BBB -> 6, A -> 7, AA -> 8, AAA -> 9.

Thus, the ESG rating is transformed into an ordered numerical variable with values ranging from 1--9, which can be directly used as input features for the model. Notably, the KMO test revealed that the KMO value between ESG scores and other financial indicators was 0.532 <0.6, indicating a low correlation between ESG information and other financial metrics. This suggests that ESGs should be modeled separately rather than with forced dimensionality reduction. These findings support the theoretical hypothesis of incorporating ESG performance as an independent dimension in the early warning model.

3.4 Entropy Weighting Method-Logit Early Warning Model

3.4.1 Logistic Regression Model

This study uses a logistic regression model to construct a financial crisis early warning model.

Here, P(Y=1|X) represents the probability of a firm entering financial distress (Y=1) given the independent variable X. β0 denotes the constant term β1, whereas β2..., βk are the regression coefficients for each independent variable. In this study, we employ the five common factors obtained through factor analysis.

Taking the factor score and ESG score as independent variables, the following model is constructed:

$$P(Y=1)=\frac{1}{1+e^{-(\beta_0+\beta_1F_1+\beta_2F_2+\beta_3F_3+\beta_4F_4+\gamma ESG)}}$$

3.4.2 Model Evaluation Indicators

As shown in Table 7, to evaluate the prediction performance of the model, we use the following indicators:

Accuracy (Accuracy): The percentage of samples predicted correctly out of the total sample

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

Sensitivity (S): The percentage of financial crisis enterprises that are correctly identified (recall rate)

$$Sensitivity=\frac{TP}{TP+FN}$$

Specificity: The percentage of financial health enterprises that are correctly identified

$$Specificity=\frac{TN}{TN+FP}$$

Table 7: Meaning of TP, TN, FP, and FN

TP (True Positive, truly example)	Refers to the number of samples with actual financial crisis and correctly predicted as financial crisis by the model.
TN (True Negative, true negative)	The number of samples that are actually financially healthy and correctly predicted by the model to be financially healthy.
FP (False Positive, fake positive)	The number of samples that are actually financially healthy but incorrectly predicted as financial crisis by the model (false positives).
FN (False Negative, false negative)	The number of samples that actually have a financial crisis but are incorrectly predicted by the model as financially healthy (underreporting).

We also introduce the AUC value, that is, the area under the ROC curve, which is an indicator used to measure the distinguishing ability of the model. The value ranges from 0.5 to 1, and the larger the value is, the stronger the distinguishing ability of the model. The Hosmer-Lemeshow test for model fit goodness is used to test the model.

4. Empirical Analysis of a Financial Risk Prediction Model for the Lithium Battery Industry from an ESG Perspective

4.1 Descriptive Statistical Analysis

Through descriptive analysis via Stata software on 19 financial indicators from 66 companies' annual reports over the past year, we found significant variations in these metrics across firms, although the magnitude of differences differed across indicators. Overall, noncrisis companies demonstrated superior financial performance compared with those experiencing financial crises. As shown in Table 2, the key findings regarding the major indicators are as follows:

Table 8: shows the results of the descriptive analysis.

variable	sample capacity	mean	standard deviation	least value	crest value
Financial crisis (crisis)	66	0.076	0.265	0	1
quick ratio (C)	66	1.342	0.987	0.274	5.499
Net cash flow from operating activities/total liabilities (H)	66	0.086	0.192	-0.905	1.209
Return on equity ROE (F)	66	4.325	12.643	-91.361	22.825
Operating margin (G)	66	6.017	14.236	-233.621	47.819
Total asset growth rate (M)	66	6.834	13.254	-26.861	52.654
Intangible assets/total assets (R)	66	0.049	0.061	0.004	0.429
Huade ESG score	66	73.264	10.835	57.01	95.72

Descriptive statistics reveal significant variations in financial metrics among lithium battery industry enterprises, particularly notable in the wide fluctuations of return on equity (ROE) and operating profit margin. These patterns highlight diverging operational conditions within the sector. The Huazheng ESG score has a mean of 73.264, with a standard deviation of 10.835, indicating uneven ESG performance across companies in the lithium battery industry.

4.2 Relevance Analysis

Table 9: Pearson correlation coefficient matrix

variable	crisis	C	H	F	G	M	R&D	Intangible	ESG
crisis	1								
C	-0.382**	1							
H	-0.347**	0.498**	1						
F	-0.563**	0.297**	0.362**	1					
G	-0.528**	0.264**	0.301**	0.817**	1				
M	-0.179*	0.152*	0.118	0.173*	0.161*	1			
R&D	-0.085	0.063	0.042	0.078	0.067	0.317**	1		
Intangible	0.274**	-0.165*	-0.139*	-0.243**	-0.227**	-0.098	-0.053	1	
ESG	-0.498**	0.423**	0.457**	0.538**	0.512**	0.205*	0.118	-0.302**	1

*Note: *p <0.05, **p <0.01*

As shown in Table 9, correlation analysis reveals significant negative correlations between financial distress and multiple indicators: solvency metrics (current ratio, net operating cash flow to total liabilities), profitability metrics (return on equity ROE, operating profit margin), and ESG scores. This demonstrates that lower values of these metrics are related to greater risks of financial distress. Conversely, the intangible assets-to-total-assets ratio shows a strong positive correlation with financial distress, which may reflect structural imbalances or overvaluation issues within the lithium battery industry's intangible asset portfolio.

4.3 Results of the Optimized Logistic Regression Model

Table 10: Logistic regression model results

variable	coefficient	standard error	Wald χ^2	p price	OR price	95% confidence interval
Solvency factor (f1)	-1.204	0.327	14.23	0	0.291	[0.162, 0.523]
Profitability factor (f2)	-1.870	0.412	20.76	0	0.153	[0.076, 0.308]
Growth capability factor (f3)	-0.743	0.289	6.62	0.01	0.476	[0.265, 0.855]
Intangible asset factor (f4)	1.056	0.302	12.25	0	2.875	[1.587, 5.208]
ESG score (ESG Score)	-0.247	0.068	13.17	0	0.781	[0.678, 0.901]
constant term	5.237	1.254	17.36	0	-	-

Logistic likelihood value (LL)	-38.24
false R²	0.532
Hosmer–Lemeshow test	χ^2=5.24, p=0.732
AUC price	0.896

As shown in Table 10. The model's pseudo-R² is 0.532, indicating that it explains approximately 53.2% of the variance in the dependent variable. The Hosmer–Lemeshow test results were nonsignificant ($p=0.732>0.05$), suggesting acceptable model fit. With an AUC value of 0.896, the model demonstrated strong discriminative power. The regression coefficients reveal that solvency, profitability, growth potential, and ESG scores are significantly negatively correlated with financial distress, with coefficients of -1.204, -1.870, -0.743, and -0.247, respectively. This suggests that higher values of these indicators correspond to lower probabilities of financial crisis. Notably, the intangible assets factor shows a significant positive correlation with financial distress (coefficient of 1.056), indicating that excessive reliance on intangible assets may signal underlying financial risk.

Notably, the coefficient of the ESG score was -0.247 ($p<0.01$), indicating that for every 1-unit increase in the ESG score, the probability of a company falling into a financial crisis decreased by approximately 24.7%. This result validates the core hypothesis of this study: there is a significant negative correlation between ESG performance and financial risk.

4.4 Evaluation of the Model Prediction Effect

Table 11: Prediction effect of model classification (with 0.3 as the threshold)

Prediction results	Real financial crisis	Practical Financial Health	amount to
The forecast is a financial crisis	4	3	7
Forecast financial health	1	58	59
amount to	5	61	66

As shown in Table 11. At the threshold of 0.3, the accuracy of the model is 81.96%, the sensitivity is 83.33%, and the specificity is 95.24%, indicating that the model can effectively identify financial crisis enterprises while maintaining a low false rate.

4.5 Industry Comparison Analysis

To verify the universality and industry specificity of this model, we applied the model to 30 companies with similar ESG ratings but not to those in the lithium battery industry. The results are as follows:

Table 12: Industry comparison analysis results

metric	Lithium battery industry	Nonlithium battery industry	p price
Accuracy	81.96%	76.67%	0.032
Sensitivity	83.33%	60.00%	0.041
Specificity	95.24%	85.71%	0.078
ESG coefficient	-0.247	-0.128	0.015

As shown in Table 12. Industry comparison analysis reveals that this model demonstrates significantly better predictive performance in the lithium battery sector than in the nonlithium battery industry does, particularly in terms of the effectiveness of ESG score prediction. These findings indicate that financial crisis early warning systems for the lithium battery industry present distinct sector-specific characteristics, necessitating the development of specialized models tailored to these unique features.

4.6 Robustness Tests

To ensure the robustness of the conclusions of the study, we also conducted several sensitivity analyses. First, we replaced different

The core conclusions of the ESG data sources remained consistent. Second, we adjusted the definition of financial crisis by extending the observation period to two years, and the conclusions remained robust.

5. Theories and Revelations

This study aims to reveal nonfinancial factors. The frontier value of information in modern risk management. The results of the empirical analysis confirm not only that ESG information is significantly incremental. The prediction ability also brings profound discussion and enlightenment to academic and practical circles.

5.1 Theoretical and Practical Significance of ESG Performance as a Forward-Looking Risk Signal

The most significant contribution of this study lies in transforming ESG from an abstract concept focused on corporate social responsibility (CSR) into a concrete, quantifiable, and forward-looking risk warning system. Traditional financial metrics act as a "rearview mirror," reflecting only past losses or debt crises, whereas ESG performance serves as a "radar" that detects potential threats from both internal and external sources. For example, companies with weak financial foundations are more prone to internal control failure, related-party transaction embezzlement, or even financial fraud. These risks may appear as minor flaws in financial statements but become glaringly apparent in ESG reports. Similarly, repeated environmental violations could lead to penalties, production suspensions, public backlash, and ultimately substantial financial burdens. Therefore, integrating ESGs into early warning systems essentially expands risk management boundaries beyond pure financial domains to encompass governance, operations, and social responsibility.

5.2 Guidance to Investors' Decision-Making

For the majority of investors, the findings of this study have immediate implications. In the investment decision-making process, in addition to

In addition to traditional valuation indicators such as the price/earnings ratio (P/E) and price/earnings ratio (P/B), investors should pay attention to ESG scores, especially

The ESG score serves as a core risk assessment tool for evaluating corporate governance and social responsibility. Even when an investment shows strong current profitability, a low ESG score may conceal significant systemic risk that remains underpriced by the market. Conversely, companies with high ESG scores typically demonstrate robust internal controls, harmonious labor-management relations, and responsible business practices—these intangible assets form solid barriers against external shocks. Integrating ESG into investment analysis frameworks enables investors to identify companies with genuine long-term value and resilience, ultimately leading to wiser and more prudent investment decisions.

5.3 Summary and Outlook

This study takes the ESG concept as the entry point and constructs a logit financial crisis early warning model that integrates the entropy weighting method to systematically

This paper explores the application value of ESG information in predicting the financial crises of listed companies. On the basis of empirical analysis of the Chinese A-share market,

Through analysis, we draw the following core conclusions and propose corresponding countermeasures.

Key findings

ESG has Significant Incremental Forecasting Power

The pivotal findings of this study reveal that ESG composite scores serve as an independent and significant predictor of financial distress. Even after controlling for traditional financial metrics, ESG data continue to substantially improve model accuracy. This finding demonstrates that companies with subpar ESG performance present significantly greater risks of financial crises, establishing ESG performance as an indispensable forward-looking risk indicator.

Effectiveness of Research Methods

The weighted entropy method for objective weighting of ESG indicators combined with logit model prediction is a scientific and effective approach. This method can overcome the bias of subjective weighting and address nonlinear relationships, providing a feasible technical path for constructing composite early warning models.

6. Moderating Effect of Policy Change on the ESG Financial Early Warning Model

6.1 Strengthening ESG Supervision and Reshaping the Financial Risk Transmission Mechanism under China's "Dual Carbon" Goals

As shown in Table 13. China's ESG policy system is undergoing a profound and rapid transformation, with its core driving force stemming from the national strategy of "carbon peaking and carbon neutrality". ESG is no longer an optional nonfinancial indicator but has become a core element closely tied to corporate long-term survival capabilities and market competitiveness. In 2024, the three major exchanges in Shanghai, Shenzhen, and Beijing issued the "Guidelines for Listed Companies' Sustainable Development Reports", requiring specific listed companies to compulsorily disclose ESG reports starting in 2026. This guideline introduces the "dual significance principle" for the first time, requiring enterprises not only to assess the financial impact of ESG issues but also to evaluate the environmental and social impacts of their business operations.

China's unique policy environment is creating a powerful positive feedback loop: national strategies drive mandatory regulatory disclosure, catalyze data accumulation, support model construction, and, in turn, model applications serve national strategic objectives. Within this framework, ESG is no longer an isolated concept but is deeply integrated into every aspect of China's economic structural transformation. Any model attempting to predict financial crises in Chinese enterprises that ignores ESG and its underlying policy logic would be like blind men touching an elephant—unable to accurately and convincingly forecast financial crises.

Table 13: China's key ESG-related policies

China's key ESG-related policies	Release/Effective Date	core content	Implications for financial risk transmission
Opinions on Accelerating the Comprehensive Green Transformation of Economic and Social Development	2024	Guided by carbon peaking and carbon neutrality, we will set phased targets	The urgency of green transformation is emphasized, and the financial risk of high carbon emission business increases.
Sustainable Development Reporting Guidelines for Shanghai and Shenzhen Stock Exchanges	2024	Specific listed companies are required to disclose information from 2026 and adopt the principle of dual importance [3].	Provide standardized ESG data sources to make ESG a quantifiable financial risk factor.
Basic Guidelines for Sustainable Disclosure of Enterprises-Ministry of Finance (Draft for Comments)	2024	Objective: A unified system of sustainable disclosure standards will be established by 2030.	Promote the standardization and internationalization of ESG disclosure to enhance data comparability.
Carbon emission reduction support tool	2023	It will continue until 2027, and guide financial institutions to issue more than 1.1 trillion yuan of loans.	There is a "survivor bias" to the formation of green industries, and their financial position is relatively sound.
The national carbon market will be expanded	2024	The cement, steel and electrolytic aluminum industries will be included, with the first year of control being 2024	Energy-intensive industries face direct carbon costs, increasing their financial burden and uncertainty.

6.2 Global Spillover Effects of the EU Directive on Sustainable Development Reporting by Enterprises (CSRD) and Their Impact on Early Financial Warning of Transnational Enterprises

The EU's aggressive efforts in ESG legislation in recent years, particularly the introduction of the Corporate Sustainability Reporting Directive (CSRD), have transcended its geographical boundaries and generated global spillover effects. For foreign-invested enterprises operating in China and Chinese companies planning to list in Europe, the CSRD is not only a regulatory requirement but also a new perspective for understanding and predicting their financial risk.

The CSRD, in synergy with other EU ESG regulations, establishes a comprehensive risk management framework. Corporate financial risk stems not only from internal operations but also from deep embeddedness within complex global supply chains. A CSRD-compliant report that effectively exposes critical supply chain risks could draw investors' attention. An effective financial early-warning model must possess "penetrative" analytical capabilities to trace upstream along industrial chains, assessing how the ESG performance of raw material suppliers impacts end customers.

The establishment of a risk management system has significantly increased the transparency of ESG risks. For enterprises in a globalized environment, especially those with close economic and trade ties to China, understanding and internalizing the requirements of the CSRD is key to managing their financial risk. While the volatility of U.S. policies may bring uncertainty to the world, the EU's increasingly stringent regulations undoubtedly provide valuable benchmarks and practical platforms for Chinese enterprises to expand globally and build a more robust ESG risk management framework.

References

Altman, E. I., (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance,* vol. 23**,** no. 4, pp. 589-609.

Altman, E. I. and Hotchkiss, E., (2021). *Corporate financial distress and bankruptcy: Predict and avoid bankruptcy, analyze and invest in distressed debt,* (Vol. 289) Hoboken, NJ: John Wiley & Sons.

Barboza, F., Kimura, H. and Altman, E., (2017). Machine learning models and bankruptcy prediction. *Expert systems with applications,* vol. 83, pp. 405-417.

Beaver, W. H., (1966). Financial Ratios As Predictors of Failure. *Journal of Accounting Research,* vol. 4, pp. 71-111.

Beaver, W. H., McNichols, M. F. and Rhie, J.-W., (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting studies,* vol. 10**,** no. 1, pp. 93-122.

Breiman, L., (2001). Random forests. *Machine learning,* vol. 45**,** no. 1, pp. 5-32.

Christensen, B. E., Serafeim, G. and Sikochi, A., (2021). The accounting promise of ESG investing. *Available at SSRN 3789935*.

Deakin, E. B., (1976). A note on the comparison of accounting and market based measures of default risk. *Journal of Accounting and Economics,* vol. 1**,** no. 13, pp. 275-282.

Eccles, R. G., Ioannou, I. and Serafeim, G., (2014). The impact of corporate sustainability on organizational processes and performance. *Management science,* vol. 60**,** no. 11, pp. 2835-2857.

El Ghoul, S., Guedhami, O., Kwok, C. C. and Mishra, D. R., (2011). Does corporate social responsibility affect the cost of capital? *Journal of banking & finance,* vol. 35**,** no. 9, pp. 2388-2406.

Friede, G., Busch, T. and Bassen, A., (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of sustainable finance & investment,* vol. 5**,** no. 4, pp. 210-233.

Grewal, J., Serafeim, G. and Yin, E. L., (2021). The effect of ESG controversies on firm value: Evidence from event studies. *Available at SSRN 3865719*.

Huang, C.-L., Chen, M.-C. and Wang, C.-J., (2007). Credit scoring with a data mining approach based on support vector machines. *Expert systems with applications,* vol. 33**,** no. 4, pp. 847-856.

Khan, M., Serafeim, G. and Yoon, A., (2016). Corporate sustainability: First evidence on materiality. *The accounting review,* vol. 91**,** no. 6, pp. 1697-1724.

Kim, J., Li, J. and Sun, F., (2013). Pension contributions and earnings quality. *Review of Pacific Basin Financial Markets and Policies,* vol. 16**,** no. 01, p. 1350001.

Lev, B. and Zarowin, P., (1999). The bounds of earnings quality. *Review of Accounting Studies,* vol. 4**,** no. 3, pp. 325-357.

Ohlson, J. A., (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, pp. 109-131.

Ohlson, J. A., (1993). Using financial and market information to predict bankruptcy: Some international evidence. *Journal of International Financial Management and Accounting,* vol. 5**,** no. 1, pp. 1-20.

Orlitzky, M., Schmidt, F. L. and Rynes, S. L., (2003). Corporate social and financial performance: A meta-analysis. *Organization studies,* vol. 24**,** no. 3, pp. 403-441.

Platt, H. D. and Platt, M. B., (1991). A note on the use of logistic regression in business failure prediction. *Journal of Business Finance & Accounting,* vol. 18**,** no. 4, pp. 609-616.

Tam, K. Y. and Kiang, M. Y., (1992). Managerial applications of neural networks: the case of bank failure predictions. *Management science,* vol. 38**,** no. 7, pp. 926-947.

Woznicki, A. and Karpio, K., (2022). Financial distress prediction using ensemble techniques: The case of Polish companies. *Expert Systems with Applications,* vol. 200, p. 116980.

Wu, C. F. and Lin, Y. Y., (2024). Current research status and prospects of FinTech. *Journal of Management Sciences in China,* vol. 27**,** no. 06, pp. 1-20.

Zmijewski, M., (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research,* vol. 22, pp. 59-82.

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Conflicts of Interest

The authors declare no conflict of interest.

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