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AI Driven Early Warning of ESG Performance in Real Estate Enterprises

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Abstract. Real estate enterprises face increasing pressure from green transition, financing constraints, and higher requirements for governance transparency. ESG performance has become an important basis for evaluating sustainable operation, risk exposure, and management quality. Due to high leverage, long development cycles, and strong externalities in the real estate industry, ESG performance deterioration often appears together with liquidity risk, weak disclosure, and governance defects. Based on Chinese A-share listed real estate enterprises from 2015 to 2024, ESG ratings, financial indicators, governance variables, and textual information from annual reports and ESG reports are integrated to build an AI-driven early-warning model for ESG performance. TF-IDF is used to extract textual risk signals. Logistic Regression, Random Forest, XGBoost, and LightGBM are compared, while SHAP is applied to explain key driving factors. The results show that LightGBM achieves the highest AUC and F1 score on the test set, indicating stronger ability to identify firms with ESG performance deterioration in the following year. Leverage ratio, cash-to-short-term debt ratio, negative risk-word frequency, environmental disclosure intensity, and governance penalty records are the main influencing factors. This framework can support ESG risk identification, internal governance improvement, and investment risk screening in real estate enterprises.

Keywords: ESG performance, real estate enterprises, AI early warning, machine learning, corporate governance

1. Introduction

Real estate enterprises are facing more complex sustainability pressure under the combined influence of green transition, financing contraction, and stronger governance transparency requirements. The industry is characterized by capital intensity, long development cycles, high leverage, and strong social externalities, which means that ESG performance changes are closely connected with liquidity risk, compliance pressure, and reputational exposure. Existing studies show that ESG rating agencies differ significantly in indicator scope, data sources, and weighting methods, leading to divergent external evaluations of the same firm's ESG performance [1]. ESG performance also has a long-term relationship with financial performance, as stronger environmental, social, and governance practices can improve capital market assessment and operational stability [2]. By integrating annual reports, ESG reports, financial indicators, governance

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variables, and textual information of real estate enterprises, an AI-driven early warning framework can transform static disclosure into predictable risk signals and identify the drivers of ESG performance deterioration in the following year.

2. Literature review

2.1. ESG disclosure research

Research on ESG disclosure mainly examines how enterprises communicate sustainable operating capacity to external stakeholders through environmental responsibility, social responsibility, and governance arrangements. Higher disclosure quality helps reduce information asymmetry and improves investors' assessment of long-term value and risk exposure. The materiality of sustainability issues also varies across industries, and ESG issues that are closely related to business operations are more likely to influence market performance and managerial decisions [3]. Research on ESG ratings of Chinese A-share listed companies further shows that different evaluation systems still vary in data completeness, industry adaptability, and indicator interpretation, so rating results need to be assessed together with firm-specific disclosure content [4]. For real estate enterprises, information on green buildings, land development, customer rights, and internal control can provide process-based signals that external ESG scores may not fully capture.

2.2. Real estate ESG risk

ESG risk in real estate enterprises has clear industry-specific characteristics. Environmental risk is concentrated in building energy consumption, green construction, carbon emissions, and land development impact. Social risk involves owner rights, community relations, employee safety, and supply chain responsibility. Governance risk is closely linked to debt pressure, related-party transactions, internal control, and disclosure quality. ESG disclosure in real estate enterprises is related to debt financing and firm value, showing that ESG performance is not only a reputational issue but also affects access to capital and market valuation [5]. Research on REITs indicates that ESG investment in real estate assets may reflect both the pursuit of financial gains and the risk of overinvestment, which requires managers to establish a dynamic balance between sustainability investment and operating efficiency [6]. During industry downturns, liquidity pressure, project delivery pressure, and governance weaknesses are more likely to develop into ESG performance volatility.

2.3. Intelligent warning models

Intelligent warning models can process high-dimensional variables and nonlinear relationships that traditional linear models cannot easily capture, making them suitable for corporate risk identification and ESG performance prediction. XGBoost improves prediction accuracy through a gradient boosting tree structure and is suitable for enterprise classification tasks involving financial, governance, and textual features [7]. LightGBM has advantages in training efficiency and generalization under large-sample and high-dimensional feature settings, which can support fast early warning modeling based on annual panel data of real estate enterprises [8]. The SHAP interpretation method decomposes model outputs into the marginal contribution of each variable to warning probability, giving managerial meaning to factors such as leverage ratio, cash-to-short-term debt ratio, weak environmental disclosure, and governance penalties [9]. When text mining is

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combined with machine learning, risk warnings, responsibility commitments, and disclosure intensity in annual reports and ESG reports can be converted into computable leading signals.

3. Experimental methods

3.1. Sample construction

The sample is selected from Chinese A-share listed real estate enterprises from 2015 to 2024. Industry classification is cross-checked according to the Shenwan real estate industry classification and the CSRC listed company industry classification. The initial sample takes listed companies that had been classified into the real estate industry during 2015–2024 as candidate firms. A total of 142 company codes are initially identified, forming a maximum possible firm-year sample of 1,420 observations. ESG performance data are obtained from Sino-Securities ESG ratings, Wind ESG, or the CSMAR ESG database. Financial and governance variables are collected from annual reports, CSMAR, and Wind. Textual materials are collected from annual reports, social responsibility reports, and ESG reports publicly disclosed on CNINFO. The sample screening is conducted sequentially. A total of 126 observations of ST firms and firms with delisting risk are excluded, 58 observations from the listing year are removed, 91 observations with missing core financial or governance variables are excluded, 104 observations with missing ESG ratings are removed, 73 observations with incomplete textual reports are excluded, and 42 observations with extreme abnormalities in core indicators such as leverage ratio and ROA are removed. The final sample includes 118 listed real estate enterprises and 926 firm-year observations. The financial, governance, and textual features in year t are then used to predict ESG performance deterioration risk in year t+1, so that the sample structure is consistent with the early-warning task and avoids future information leakage.

3.2. Feature engineering

Feature engineering is developed around structured indicators and unstructured textual indicators. Structured indicators include leverage ratio, cash-to-short-term debt ratio, ROA, revenue growth, ownership concentration, board independence, audit opinion, and regulatory penalty records. Textual indicators are extracted from annual reports and ESG reports. The keywords include green building, environmental commitment, customer complaint, work safety, internal control, and risk warning [10]. Disclosure intensity, risk-word frequency, and textual sentiment are also calculated. The TF-IDF method is used to measure the relative importance of keywords in each firm-year text, as shown in Formula (1).

$$TF-IDF_{i,t,k}=\frac{n_{i,t,k}}{\sum_{k=1}^{K} n_{i,t,k}} \times \log\left(\frac{N}{1+d_k}\right) \tag{1}$$

In Formula (1), $n_{i,t,k}$ denotes the frequency of keyword k in firm i's text in year t. K denotes the total number of keywords. N denotes the total number of sample documents. d_k denotes the number of documents containing keyword k.

The early-warning label is defined according to ESG rating downgrade in the following year, ESG ranking falling into the bottom 30% of the industry, or the occurrence of environmental penalties and major governance-related negative events, as shown in Formula (2).

$$Y_{i,t+1}=I\left(\Delta ESG_{i,t+1}<0 \vee Rank\left(ESG_{i,t+1}\right)\leq 30\% \vee Penalty_{i,t+1}=1\right) \tag{2}$$

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In Formula (2), $Y_{i,t+1}$ denotes the ESG risk label in the following year. $I(\cdot)$ is the indicator function. $\Delta ESG_{i,t+1}$ denotes the change in ESG rating or score. $Penalty_{i,t+1}$ denotes whether a penalty or major negative event occurs.

3.3. Model training

Model training follows a time-series sample split. Data from 2015 to 2021 are used for training, data from 2022 are used for validation, and data from 2023 to 2024 are used for testing. This design avoids future information leakage caused by random splitting. Logistic Regression is used as the linear baseline model. Random Forest is used to test the effect of a nonlinear tree-based model. XGBoost and LightGBM are used to compare the predictive ability of gradient boosting models under high-dimensional features [11]. The training process includes missing value imputation, continuous variable normalization, categorical variable encoding, textual feature concatenation, class imbalance processing, and model parameter tuning. The validation set is used to adjust tree depth, learning rate, number of leaf nodes, and regularization parameters. The test set is only used for final evaluation. The evaluation metrics include Accuracy, Precision, Recall, F1, and AUC. Recall is used to measure the ability to identify risk firms. AUC is used to evaluate the overall discriminatory ability of the model. SHAP is used to explain the contribution direction and strength of each variable to the early-warning probability.

4. Results

4.1. Predictive performance

The model prediction results are shown in Table 1. Logistic Regression achieves an AUC of 0.742, which indicates that the linear model can identify part of the ESG deterioration risk. Its ability to capture nonlinear relationships among financial pressure, governance defects, and textual risk signals is limited. Random Forest increases the AUC to 0.824, with an F1 value of 0.720. This result shows that the tree-based model improves classification performance under multi-source variables. XGBoost further increases the AUC to 0.861, with Recall reaching 0.748. This suggests that the gradient boosting mechanism can identify potential risk firms more effectively. LightGBM achieves the highest AUC of 0.879 and the highest F1 value of 0.776. Its Recall reaches 0.782, which means that it can identify about 78.2% of ESG risk firms in the test set. Its Precision remains at 0.771, so the false alarm level is within an acceptable range. Overall, the results show that nonlinear ensemble models integrating financial, governance, and textual features are more suitable for the early warning of ESG performance in real estate enterprises.

Table 1. Comparison of model prediction performance

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	0.713	0.668	0.612	0.638	0.742
Random Forest	0.781	0.734	0.706	0.720	0.824
XGBoost	0.807	0.759	0.748	0.753	0.861
LightGBM	0.823	0.771	0.782	0.776	0.879

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4.2. Warning interpretation

The SHAP interpretation results of the LightGBM model are shown in Figure 1. The SHAP values of the leverage ratio are mainly distributed in the positive range, with a mean value of about 0.083. This indicates that high leverage significantly increases the probability of ESG performance deterioration in the following year for real estate enterprises. The SHAP values of the cash-to-short-term debt ratio are concentrated in the negative range, with a mean value of about -0.071. This shows that stronger short-term debt-paying capacity reduces the early-warning probability. The mean value of negative risk-word frequency is about 0.066. This suggests that when words related to debt pressure, litigation, penalties, and delivery risk appear frequently in annual reports and ESG reports, the model raises the risk prediction. Environmental disclosure intensity and green building disclosure show negative contributions, which reflects that continuous environmental responsibility disclosure can reduce deterioration risk. The mean contribution of governance penalty records is about 0.052, indicating that governance violations can serve as direct leading signals of ESG deterioration. This result is consistent with the setting of financial, governance, and textual variables in feature engineering.

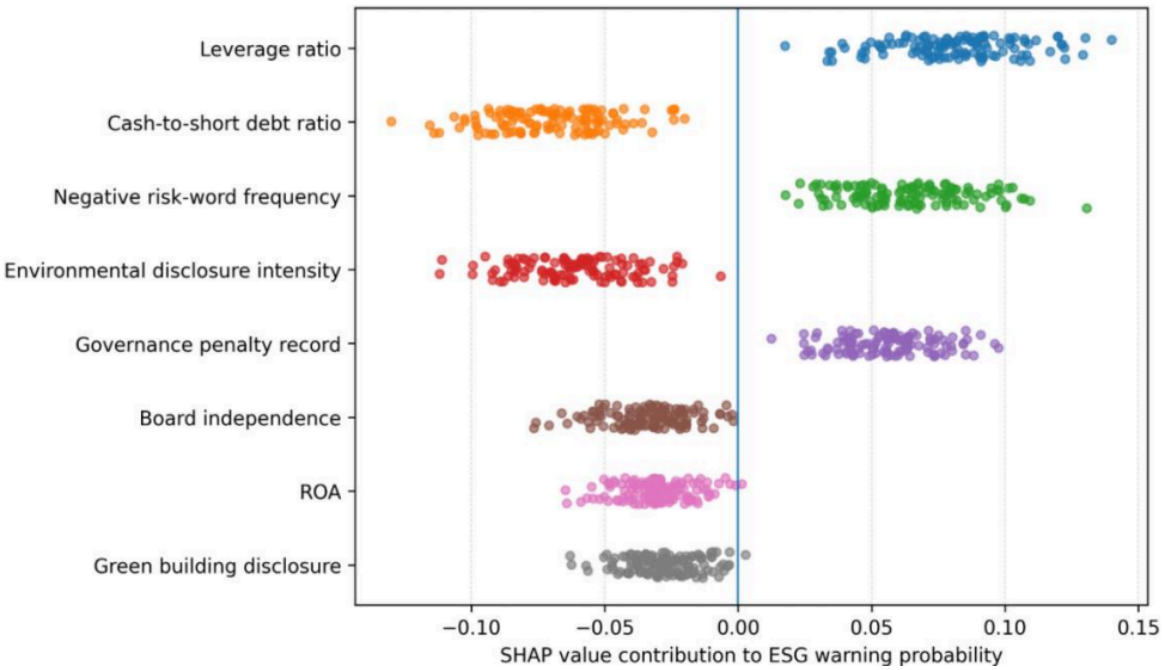

Figure 1. SHAP distribution of key early-warning factors

5. Discussion

The experimental results indicate that ESG performance deterioration in real estate enterprises is not determined by a single environmental indicator. It is jointly driven by financial pressure, governance stability, and information disclosure quality. LightGBM performs better than the linear model, which shows that ESG risk has clear nonlinear and compound characteristics. Firms with high leverage are more likely to experience ESG deterioration when short-term debt-paying capacity is weak. The SHAP results further show that negative risk-word frequency and governance penalty records can reflect potential corporate risks in advance. Textual information in annual reports and ESG reports therefore has early-warning value. Environmental disclosure intensity and green building disclosure

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show negative contributions, suggesting that continuous and specific environmental responsibility disclosure can reduce the predicted risk probability. This result indicates that ESG management in real estate enterprises should move beyond annual ratings and include financial resilience, governance compliance, and disclosure quality in a dynamic monitoring system.

6. Conclusion

An AI prediction framework is developed for the early warning of ESG performance in real estate enterprises by integrating financial data, governance variables, and textual information. The sample is based on Chinese A-share listed real estate enterprises from 2015 to 2024. A firm-year panel sample is formed through sequential screening, and features in year t are used to predict ESG performance deterioration risk in year t+1. The methodology combines TF-IDF textual features, machine learning classification models, and SHAP interpretation, forming a complete process from data collection and feature construction to model training and result interpretation. The results show that LightGBM has strong predictive performance. Leverage ratio, cash-to-short-term debt ratio, negative risk-word frequency, environmental disclosure intensity, and governance penalty records are the main early-warning factors. This framework is operational and can be applied to internal ESG risk monitoring, investment risk screening, and regulatory decision support.

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