The Mechanism analysis of Corporate Financial Risk Influences via BiLSTM-MAttention Model

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Abstract. Against the backdrop of increasing macroeconomic volatility and growing complexity in corporate operating environments, exploring the intrinsic mechanisms underlying financial risk factors is of great significance for enhancing firms' capabilities in risk identification and prevention. Based on quarterly data of Chinese A-share listed companies from 2020 to 2024, this study proposes a BiLSTM-MAttention model constructed on quarterly financial indicators. Compared with prior studies relying on annual reports, quarterly data enable the model to capture the dynamic fluctuations of corporate financial risks with higher frequency, thereby improving its sensitivity and timeliness in risk detection. The BiLSTM structure effectively extracts temporal dependencies among financial indicators, while the Multi-Head Attention mechanism (MAttention) further achieves deep feature integration and adaptive weight allocation, strengthening the model's ability to identify financial risks. Furthermore, the SHapley Additive exPlanations (SHAP) approach is introduced to enhance model interpretability by quantifying the marginal contribution of each financial indicator to the prediction results, thereby revealing the underlying mechanisms of risk formation. Empirical results demonstrate that the proposed model not only outperforms traditional interpretable machine learning models in predictive accuracy but also elucidates the heterogeneous predictive importance of various indicators at the feature level. These findings provide valuable insights for government regulators and corporate managers in improving financial risk prevention frameworks and enhancing overall risk governance capacity.

Keywords: Financial Risk, Explainability Analysis, Deep Learning, BiLSTM-MAttention Model.

1. Introduction

In the increasingly complex and volatile economic market and corporate operating environment, accurately identifying and analyzing the formation mechanisms of corporate financial risk has become a core issue in the fields of financial management and risk control, as well as a focal point of broad concern across society. Financial risk refers to the possibility that uncertainties arising from factors such as capital raising, investment decisions, capital structure, working capital management, and changes in the external economic environment may cause deviations between a firm's actual and expected returns, potentially leading to financial deterioration, capital losses, or even bankruptcy and liquidation. With the rapid advancement of neural network technologies, both academia and industry have increasingly integrated them with machine learning methods to construct more intelligent and precise models for financial risk identification. In recent years, Lu et al. [1] proposed an internal control defect identification approach based on corporate profiling and machine learning, demonstrating the effectiveness of intelligent algorithms in extracting complex financial risk features. Long and Chen [2] developed a corporate financial risk early warning model, providing an operational empirical framework for subsequent studies. Tian et al. [3], from the perspective of quantitative detection of financial fraud, further expanded the application of machine learning in financial risk identification.

Early studies on the determinants of corporate financial risk were mostly conducted based on econometric models. Altman (1968) proposed the Z-Score model, which employs multivariate discriminant analysis to predict corporate bankruptcy risk. Ohlson (1980) later developed the O-Score model using a Logit regression framework to estimate the conditional probability of a firm falling into financial distress. These econometrics-based approaches have provided significant theoretical and empirical value in the study of corporate financial risk. However, as noted by Liu [4], the establishment of a comprehensive financial risk identification and prevention system is the foundation for preventing systemic risks, yet traditional econometric models often fail to capture nonlinear and dynamic dependencies among financial variables, thereby limiting both their explanatory power and predictive accuracy. Yang et al. [5] pointed out that conventional models struggle to capture the nonlinear dependencies among financial variables. Therefore, it is necessary to introduce new modeling approaches that can accommodate nonlinear structures, capture temporal dynamics, and maintain interpretability, in order to more scientifically uncover the mechanisms through which financial indicators influence corporate financial risk.

Meanwhile, with the continuous advancement of machine learning and deep learning technologies, a variety of interpretable machine learning models have been widely applied to the study of financial risk formation mechanisms. Zhao and Zhang [6] combined MD&A textual information with deep learning models to reveal the role of semantic information in financial fraud detection. Liu et al. [7] examined corporate financial fraud risk from the perspective of independent directors and employed machine learning models to predict such risks, thereby validating the effectiveness of applying artificial intelligence methods to the integrated study of corporate governance and risk identification. Wu et al. [8], Zhou et al. [9], and Liu et al. [10] conducted financial risk identification research based on models such as Random Forest, XGBoost, and LightGBM, quantitatively assessing the contribution of various indicators to risk through feature importance analysis, thereby improving the predictive accuracy and interpretability of their models. However, most existing studies still rely primarily on annual financial statement data as the main source of information. This low-frequency data structure fails to comprehensively capture the dynamic changes in a firm's operating conditions within a fiscal year, resulting in insufficient information granularity and limited timeliness in financial risk identification and prediction.

In view of the limitations of the existing research, this study builds upon the work of Chen et al. [11], who employed an LSTM model to measure credit bond default risk and laid the foundation for applying deep sequential models in financial risk prediction. On this basis, a BiLSTM-MAttention–based analytical framework is proposed to investigate the mechanism influencing corporate financial risk. Specifically, at the data level, quarterly-frequency information is introduced to capture the dynamic evolution of firms' financial conditions with higher temporal resolution, thereby enhancing the model's sensitivity and responsiveness to risk fluctuations. In terms of model architecture, the BiLSTM network is utilized to fully exploit the sequential dependencies in quarterly financial data, enabling the identification of both forward and backward effects of financial indicators on risk. Moreover, the MAttention is incorporated to allocate random and associative effects across variables, strengthening the model's capacity to represent nonlinear and interactive relationships. Building on this framework, the SHAP (Shapley Additive Explanations) method is applied to visualize and interpret model outputs by quantifying the marginal contributions of each financial indicator to the prediction results, thereby revealing the mechanisms and predictive significance of various factors in the formation of financial risk. Empirical results demonstrate that the proposed model significantly outperforms traditional interpretable machine learning approaches in predictive accuracy, exhibiting superior stability and generalization ability. Furthermore, SHAP-based interpretability analysis highlights the central roles of governance capability and cash flow strength in financial risk identification, confirming the model's effectiveness in both feature interpretation and mechanism characterization. Overall, this study integrates sequential modeling with explainable analysis in an innovative manner and provides a novel technical pathway and policy insight for the dynamic identification and precise prevention of corporate financial risk.

2. Theoretical Basis and Methodology

In the field of deep learning, Song [12] developed a financial distress prediction model based on PCA-BiGRU-Attention, which provides valuable methodological insights for the architectural design of this study. Considering that quarterly financial data in corporate risk prediction scenarios exhibit significant temporal dependency and inter-period correlation, this study extends that framework by constructing a BiLSTM-MAttention model that integrates bidirectional long short-term memory networks with multi-head attention mechanisms. The proposed model aims to address the limitations of single sequential models (e.g., LSTM), which can only capture local temporal patterns and fail to model cross-quarter global dependencies. Meanwhile, it mitigates the instability of pure attention-based architectures when applied to relatively small samples with short time steps. Through this design, the BiLSTM-MAttention model enables high-precision identification of corporate financial risk with enhanced temporal representation and learning robustness.

2.1. Input Data Layer: Construction of Quarterly Financial Feature Sequences

Let the quarterly financial feature matrix of the i-th company be defined as:

$$X_i = [x_{i1}, x_{i2}, x_{i3}, x_{i4}]^{\mathrm{T}} \in R^{T \times K} \tag{1}$$

where T denotes the four quarters in a year, K represents the dimensionality of financial features for each quarter, and $x_{\mathrm{it}} \in R^{\mathrm{K}}$ represents the feature vector for the t-th quarter.

The overall shape of the input tensor is:

$$X \in R^{(batch\_\mathrm{size}, \mathrm{T}=4, \mathrm{K})} \tag{2}$$

This represents a data structure of “batch of companies × 4 quarters × K financial features”.

2.2. Bidirectional LSTM Layer: Extracting Local Dynamic Features Across Quarters

Corporate financial risk often manifests as gradual deterioration or abrupt changes across quarters. The BiLSTM network can simultaneously capture the trend of financial indicators in chronological order (Q1 → Q4) and the sources of risk propagation in reverse order (Q4 → Q1).

The forward and backward recurrence formulas of BiLSTM are defined as:

$$\rightarrow h_t = LSTM_{f(x_t, \rightarrow h_{\{t-1\}})}, \quad \leftarrow h_t = LSTM_{b(x_t, \leftarrow h_{\{t+1\}})} \tag{3}$$

and are concatenated to obtain:

$$h_t = [\rightarrow h_t; \leftarrow h_t] \in R^{\{2d_h\}} \tag{4}$$

where d_h denotes the hidden layer dimension of the unidirectional LSTM.

The final output matrix is:

$$H = [h_1, h_2, h_3, h_4]^T \in R^{T \times 2dh} \tag{5}$$

2.3. Standardization and Denoising

Financial data often exhibit substantial scale differences across firms and quarters, and may contain noise or outliers (e.g., end-of-quarter adjustments or one-off gains and losses). To enhance model robustness, the BiLSTM outputs are processed in two steps:

Step 1: Batch normalization

$$\hat{\mathrm{h}}_t = \frac{(h_t - \mu_B)}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{6}$$

where μ_B and σ_B^2 denote the mean and variance of the current batch, used to eliminate numerical discrepancies between different firms.

Step 2: Nonlinear activation and stochastic dropout

$$h_t' = ReLU(\hat{\mathrm{h}}_t) \tag{7}$$

During training, Dropout is applied to prevent the model from overfitting to occasional anomalies in a single quarter.

2.4. Multi-Head Attention Layer: Modeling Inter-Quarter Financial Dependencies

Given that corporate financial risk formation exhibits inter-period causality (e.g., an investment error in Q1 may manifest as a cash flow risk in Q3), a multi-head self-attention mechanism is introduced to capture global interactions across quarters. The attention computation is defined as:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{8}$$

where $Q,K,V \in R^{T\times d_k}$ represent the Query, Key, and Value matrices, respectively.

Under the multi-head mechanism:

$$Mhead(H) = [head^1;\ head^2;\ \dots;\ head_m]W^O \tag{9}$$

where $head_i = Attention\left(H\,W_i^Q, H\,W_i^K, H\,W_i^V\right)$

Finally, the output of the multi-head attention layer is represented as:

$Z = Mhead(H') \in R^{T\times d_z}$ (10)

2.5. Classification Layer: Generating Financial Risk Probability Outputs

After multi-layer sequential feature extraction and inter-quarter dependency modeling, the quarterly features need to be aggregated to generate the annual financial risk probability for each firm. This study employs global pooling followed by a two-layer fully connected network.

The global average pooling operation extracts the firm's aggregated risk representation across the four quarters:

$$Z_{pool} = \frac{1}{T}\sum_{t=1}^{T} Z_t \tag{11}$$

A fully connected network with ReLU activation and Sigmoid output is then applied:

$$y_i = \sigma\left(W^2 \cdot ReLU\left(W^1 z_{pool} + b^1\right) + b^2\right) \tag{12}$$

where $y_i \in [0,1]$ represents the probability that firm i will experience financial risk in the year.

3. Empirical Analysis

3.1. Data Sources and Feature Selection

The data used in this study are obtained from the CSMAR (China Stock Market & Accounting Research) database, covering the quarterly financial statements of China's A-share listed companies from 2020 to 2024. This period spans both the pandemic shock and the subsequent economic recovery, allowing for a comprehensive reflection of the dynamic evolution of corporate financial risk. Prior research by Xia and Shen [13], which employed textual information from internal control self-assessment reports to predict financial distress, has highlighted the potential value of financial reporting narratives in risk identification.

To comprehensively evaluate firms' financial conditions, this study selects 33 representative indicators from five dimensions, namely solvency, operational efficiency, profitability, cash flow capability, and growth capability, providing a solid foundation for model training and risk identification analysis. The specific indicators are listed in Table 1.

Table 1. Descriptive Statistics of Selected Financial Indicators

Indicator Category	Financial Indicator	Symbol	Direction
Corporate Governance	Total number of regulatory personnel	X1	–
	Board size	X2	–
	Number of senior executives	X3	–
	Total board compensation	X4	–
	Total supervisory board compensation	X5	–
	Total executive compensation	X6	–
	Largest shareholder ownership ratio	X7	–
	Top ten shareholders' ownership ratio	X8	–
Solvency	Current ratio	X9	Positive
	Quick ratio (acid-test ratio)	X10	Positive
	Cash ratio	X11	Positive
	Interest coverage ratio	X12	Positive
	Debt-to-asset ratio	X13	Negative
Operating Efficiency	Accounts receivable turnover	X14	Positive
	Inventory turnover	X15	Positive
	Accounts payable turnover	X16	Positive
	Current assets turnover	X17	Positive
	Fixed assets turnover	X18	Positive
	Total assets turnover	X19	Positive
Profitability	Return on assets (ROA)	X20	Positive
	Net profit margin on total assets	X21	Positive
	Return on equity (ROE)	X22	Positive
	Return on invested capital (ROIC)	X23	Positive
	Operating profit margin	X24	Positive
Cash Flow Capability	Net profit cash content	X25	Positive
	Operating revenue cash content	X26	Positive
	Cash flow to shareholders from financing activities	X27	Negative
	Total cash collection rate	X28	Positive
Growth Capability	Fixed asset growth rate	X29	Positive
	Total asset growth rate	X30	Positive
	Net profit growth rate	X31	Positive
	Operating revenue growth rate	X32	Positive
	Sustainable growth rate	X33	Positive

Note: All indicators are selected with reference to relevant financial analysis literature and practical standards. They are classified as positive or negative indicators according to their economic interpretation, facilitating subsequent model identification and normalization.

The first step in data processing involved removing financial firms and samples with severely missing financial data to ensure the representativeness and quality of the dataset. Subsequently, to construct a unified data matrix and enhance data consistency and validity, the raw quarterly financial data underwent systematic preprocessing. For the small number of missing values in the sample, an imputation method based on the Random Forest algorithm was employed. This approach uses the correlations among financial indicators as input features to train a Random Forest regression model to predict missing values, thereby maintaining the stability of the original data structure while significantly improving imputation accuracy. To eliminate differences in scale and magnitude across indicators, min-max normalization was applied to all variables, mapping their values to the [0,1] range, which ensures comparability among the financial indicators.

The second step aimed to comprehensively reflect the information content and discriminative power of each indicator. The CRITIC method was employed to calculate the coefficient of variation and correlation intensity for each indicator, thereby determining their objective weights. Based on the weighted product of standardized indicator values and their corresponding weights, composite scores were computed for each firm across the five dimensions: solvency, operational efficiency, profitability, cash flow capability, and growth capability. These five-dimension scores were then merged with the firms' quarterly information to construct a complete quarterly panel dataset, providing a quantitative foundation for the subsequent training and empirical analysis of the BiLSTM-MAttention model. All data processing, indicator measurement, and model computations were conducted in Python 3.9, with core code implemented in the Jupyter Notebook environment within Visual Studio Code.

3.2. Model Performance Comparison

To evaluate the effectiveness and superiority of the proposed BiLSTM-MAttention model in corporate financial risk prediction, it was systematically compared with three representative traditional interpretable ensemble learning models: XGBoost, LightGBM, and Random Forest. Using the same dataset and feature set for training and testing, the classification performance and robustness of each model in financial risk prediction were comprehensively assessed. The results are presented in Table 2.

Table 2. Comparison of Prediction Performance Across Models

	Accuracy	F1Score	AUC
BiLSTM-Mattention Model	0.8571	0.8148	0.9520
XGBoost	0.8000	0.6316	0.8880
LightGBM	0.7714	0.6800	0.8667
RandomForest	0.8143	0.7111	0.8587

Note: Accuracy measures the overall proportion of correct predictions and provides a direct assessment of the model's general classification performance. The F1 score is the harmonic mean of precision and recall, reflecting the model's ability to balance correctly identifying positive samples and avoiding false negatives. The AUC (Area Under the ROC Curve) quantifies the model's discriminative capability across different classification thresholds; a higher AUC indicates a clearer distinction between high-risk and low-risk firms and greater model stability.

The comparative analysis indicates that the proposed BiLSTM-MAttention model significantly outperforms traditional interpretable ensemble learning models in corporate financial risk prediction. It achieves an accuracy of 0.8571, higher than that of XGBoost, LightGBM, and Random Forest. The F1 score of 0.8148 demonstrates superior capability in identifying high-risk firms, while the AUC of 0.9520 indicates clearer and more stable discrimination between risky and non-risky firms. This superior performance is primarily attributable to the ability of BiLSTM to capture sequential temporal features and the multi-head attention mechanism's capacity to weight key financial indicators, enabling the model to better handle nonlinear relationships and dynamic feature patterns compared with ensemble learning methods that rely solely on static features. Overall, the model exhibits significant advantages in accuracy, robustness, and interpretability, providing an effective tool for corporate financial risk prediction.

3.3. Predictive Feature Importance Analysis

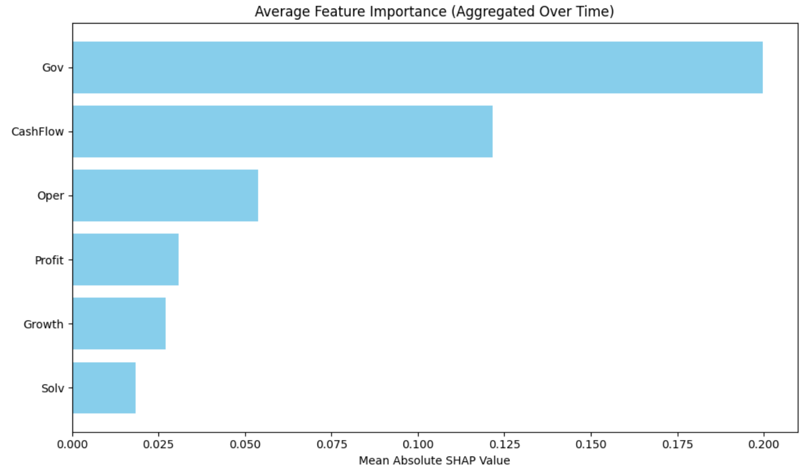

Figure 1. Average feature Importance Ranking Across Different Financial Capability Dimensions

As shown in Figure 1, the average feature importance aggregated over time clearly ranks the financial capability dimensions as follows: Corporate Governance (Gov) > Cash Flow Capability (CashFlow) > Operating Efficiency (Oper) > Profitability (Profit) > Growth Capability (Growth) > Solvency (Solv). This result indicates that internal governance quality and cash flow stability are the most critical determinants in financial risk identification. Governance indicators reflect the quality of internal controls and decision-making transparency, while cash flow capability indicators directly capture a firm's liquidity safety and dependence on external financing. Both dimensions demonstrate significant explanatory power and predictive value for corporate financial risk.

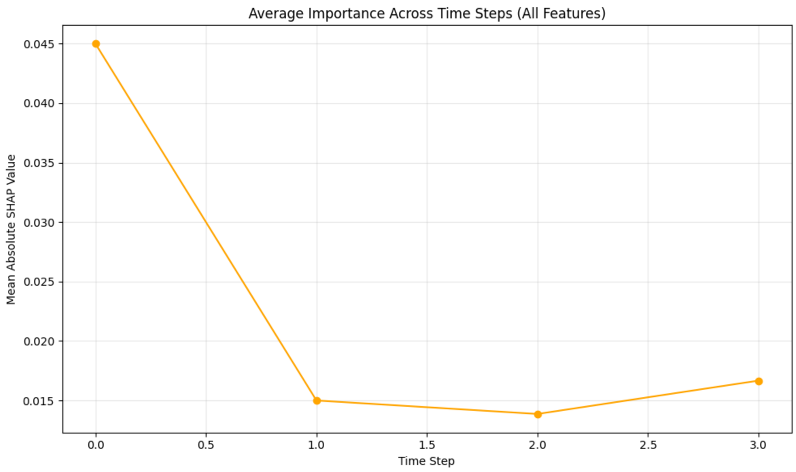

Figure 2. Temporal Trends of Average Feature SHAP Values Across Different Time Steps

As illustrated in Figure 2, the average SHAP values across different time steps exhibit a clear declining trend: the mean absolute SHAP value at t0 is approximately 0.045, substantially higher than those at t1–t3 (around 0.015–0.017). This indicates that the model relies most heavily on the current-period data when identifying financial risk, while the marginal contribution of historical information gradually diminishes. These findings are consistent with the real-world characteristics of corporate financial risk, where the most recent financial conditions more directly reflect a firm's debt repayment pressure and liquidity status.

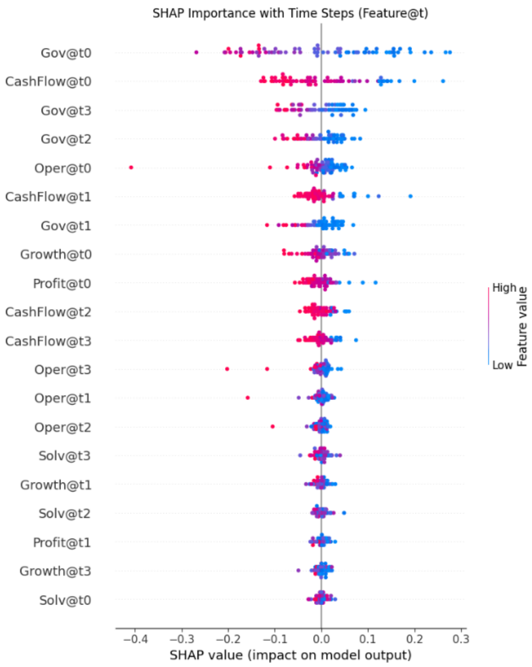

Figure 3. SHAP Value Importance Distribution of Core Financial Capability Features Across Quarters

As shown in Figure 3, the model assigns the highest importance to features in the most recent period (t0), indicating that it primarily relies on the firm's current financial characteristics to assess risk. Among these, Gov@t0 (corporate governance) and CashFlow@t0 (cash flow capability) have the most significant impact on model outputs, highlighting that governance quality and cash flow stability are key determinants of financial risk. Features from the lagged periods (t1 and t3) still exert some influence, reflecting the temporal continuity and dynamic correlation of financial risk, as past financial performance continues to affect subsequent risk exposure.

Overall, the BiLSTM-MAttention model demonstrates strong convergence and robustness during training. The SHAP-based interpretability analysis reveals the predictive contribution of different financial indicators in risk identification. The results confirm that governance and cash flow capability are critical determinants of corporate financial risk, with the model showing the greatest reliance on current-period financial information. This validates the effectiveness of the proposed deep learning framework integrating sequential modeling and attention mechanisms for dynamic financial risk prediction.

4. Conclusions and Implications

This study develops an interpretable deep learning model integrating time-series features (the BiLSTM-MAttention) for dynamic identification of corporate financial risk based on panel financial data. Compared with traditional interpretable ensemble learning models (XGBoost, LightGBM, and Random Forest), the results indicate that the proposed model achieves significant advantages in overall predictive performance. This demonstrates that combining temporal dependency structures with deep interpretability mechanisms can more effectively capture the dynamic evolution of corporate financial indicators, thereby enhancing the scientific rigor and foresight of risk prediction.

At the current stage of economic development, robust corporate governance, effective internal controls, and cash flow security have emerged as key determinants of financial stability. In contrast, traditional ratio-based risk identification methods often overlook governance and liquidity dimensions, failing to reveal the true transmission pathways of financial risk. Through dynamic learning, the proposed model not only enables more precise characterization of overall risk but also uncovers individualized risk features according to firm type, such as cash flow indicators contributing more to risk assessment in capital-intensive firms, whereas profitability and growth indicators are more representative in innovation-driven firms.

In summary, the BiLSTM-MAttention model outperforms traditional methods in predictive accuracy and enables a transition in financial risk identification from static to dynamic and from aggregate to individual levels. Future research can further incorporate macroeconomic variables and multi-source heterogeneous data, expand the model's predictive capability and provide empirical evidence and decision-making support for firms to enhance internal governance, strengthen risk management, and develop targeted risk prevention strategies.

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