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Research on Dynamic Assessment of Accounts Receivable Default Risk Using Long Short-Term Memory Network (LSTM) Combined with Attention Mechanism

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ABSTRACT Dynamic assessment of accounts-receivable default risk requires time-series modeling of nonlinear financial and transaction behaviors. This study develops a Long Short-Term Memory network combined with an attention mechanism for early default-risk prediction. Financial and transaction data from 2844 manufacturing supply-chain enterprises over 72 consecutive months are preprocessed using seasonal decomposition, normalization, leakage-controlled feature construction, and imbalance correction. A three-layer LSTM extracts temporal dependence from 42 variables within a 12-month observation window, while the attention mechanism adaptively weights key time steps for interpretable risk classification. Experimental comparison with logistic regression and traditional LSTM shows that the LSTM–attention model achieves an accuracy of 0.892, recall of 0.874, F1 score of 0.878, and AUC of 0.921. Feature-weight analysis identifies aging structure, accounts-receivable turnover, leverage, and cash-flow ratio as key risk indicators. The model provides an engineering-oriented framework for financial time-series signal modeling, intelligent risk warning, and decision support.

INDEX TERMS lstm, attention mechanism, default risk prediction, time-series modeling, decision support

I. INTRODUCTION

WITH the economic restructuring and the deepening of the market credit system, the commercial credit transactions between enterprises are becoming more and more frequent. Accounts receivable being an important part of a company's current assets, in turn, have a direct effect on its cash flow and stability in business operations. Accounts receivable default risk can be described as the potential for economic loss to creditors because of the insolvency of debtors who do not honour their payment commitments on time. In recent years, the scale of corporate accounts receivables has continued to grow, and the occurrence of defaults has become more common, which increases the requirements for the risk management capability of financial institutions and enterprises themselves.

Traditional methods of assessing accounts receivable risk incorporate substantial use of expert experience and static analysis of financial statements. The results of the assessment are often behind changes in the actual operating conditions of the company, so the dynamic monitoring of risks and early warning are difficult. While, statistical learning-based assessment models like logistic regression, or decision trees enhance the predictive capabilities to some extent, those methods hardly have the capacity to extract dynamic features from time series data. With the rapidly developed big data and artificial intelligence technologies, deep learning model has shown unique advantages in processing time series data. Long Short-Term Memory (LSTM) networks, being special recurrent neural network structures, can effectively capture long-term dependency in time series information and it is apt to understand the temporal evolution patterns of time series information of corporate finance data.

To further improve model ability to detect significant time points, attention mechanism is added, which allows the model to automatically pay attention to feature dimension and time point with higher contribution to default prediction in multiple time steps. The inclusion of the attention mechanism also makes the model more interpretable and accurate for predicting the time series data. Based on the LSTM and attention mechanism, .based on the LSTM and attention mechanism, this study establishes a dynamic assessment model for accounts receivables default risk, which forms a comprehensive research framework spanning data preprocessing, model construction, training optimization, and result verification.

II. RELATED WORK

Financial risk management (FRM) is considered a core function in banking, insurance and general corporate finance, but its specific practices vary significantly across different industries and contexts. Landi et al. [1] explored the impact mechanism of ESG ratings on corporate financial risk levels after embedding sustainability into the risk management framework. Chandran et al. [2] reviewed the evolution of research on the integration of climate change risk and corporate financial risk. Moridu [3] adopted a qualitative perspective to focus on how listed companies identify, assess and respond to financial risks through corporate governance practices. Nugroho [4] used the isolated forest algorithm to construct an anomaly detection model for corporate balance sheets and verified the model's effectiveness by comparing it with actual financial crisis events. Although financial risk management (FRM) is considered a core function in banking, insurance and general corporate finance, there are differences in the specific practices of risk identification, assessment and mitigation across different industries. Idris [5] explored financial risk management practices in cross-industry contexts, revealing commonalities and industry characteristics.

Ammer and Sattarov [6] collected response data from institutional and individual investors to different governance structures and information disclosure levels, and used structural equation modeling to analyze the relationship between governance, transparency and decision quality. Judijanto et al. [7] developed an early warning system based on machine learning to identify signals of financial distress. Nurjanah and Arifa [8] used corporate maturity and financial risk as contextual factors to re-examine the relationship between CSR disclosure and corporate value. Alzayed et al. [9] used empirical research methods, used panel data of large listed companies to construct a multi-dimensional governance index, and distinguished between systemic risk and non-systemic risk, active risk-taking and passive risk exposure. Rumasukun and Noch [10] focused on the banking, insurance and general corporate finance sectors, and systematically explored the practical characteristics and industry differences of the three core links of risk identification, assessment and mitigation. This paper proposes to use long short-term memory network (LSTM) combined with attention mechanism to construct a dynamic assessment model of corporate accounts receivable default risk, aiming to achieve adaptive tracking and interpretable early warning of risk status through time-series deep learning methods.

III. METHODS

A. DATA ACQUISITION AND PREPROCESSING

This study selected accounts receivable data from 3,000 companies in a manufacturing supply chain from January 2018 to December 2023 as the research object. Data sources included internal financial statements, supply chain transaction records, and publicly available external credit information. The raw data covered 42 dimensions, including accounts receivable balance, aging structure, collection cycle, sales revenue, debt-to-equity ratio, current ratio, quick ratio, interest coverage ratio, company size, and industry prosperity index, forming a total of 72 months of time-series data.

During the data cleaning phase, 156 companies with severely missing or outlier values were removed, ultimately retaining data from 2844 companies. For missing values, time series interpolation was used to impute them, ensuring continuity over time. To account for the inherent periodicity in manufacturing supply chain data, a seasonal decomposition procedure (STL) was applied to the 72-month sequence to remove seasonal fluctuations and isolate the underlying trend and residual risk signals. Some financial indicators were normalized to eliminate the influence of unit dimensions; the maximum-minimum normalization method was used to map the data to the 0-1 range. A default label was defined, marking companies that had not paid accounts receivable for more than three consecutive months or had an overdue rate exceeding 30% as defaulting samples. To prevent label leakage, the feature set used for prediction was strictly limited to financial and behavioral data observed prior to the 90-day threshold; specifically, the 'aging structure' feature was redefined as the proportion of accounts receivable overdue for 30–60 days to ensure the model predicts future default rather than identifying existing default status. Ultimately, the defaulting sample ratio was 12.7%, while the non-defaulting sample ratio was 87.3%. To address the sample imbalance issue, the SMOTE algorithm was used to oversample the defaulting samples, achieving a default-to-non-defaulting sample ratio of 1:3. We acknowledge that synthetic oversampling may introduce noise into individual time steps; however, post-sampling validation was conducted to ensure that the synthetic series maintained the statistical trend and covariance structure of the original defaulting samples, minimizing the disruption of logical continuity in the financial time series.

B. TEMPORAL FEATURE EXTRACTION BASED ON LSTM

A three-layer LSTM network structure was constructed to extract time-series features of corporate accounts receivable risk. The input dimension was set to 42 feature variables, and the time step was set to 12 months, that is, the default status of the next 3 months was predicted by the time-series data of the past 12 months of the enterprise. The first layer of LSTM was set with 128 hidden units, and the activation function was tanh function. This layer output complete time-step sequence information. The second layer of LSTM was set with 64 hidden units and returned sequence information to support the access of the attention mechanism. The third layer of LSTM was set with 32 hidden units and output time-series feature vector [11,12].

To prevent overfitting, a Dropout layer is added after each LSTM layer, with a dropout rate set to 0.3. The model input layer receives three-dimensional tensor data with a shape of (batch size, time step, feature dimension). The LSTM layer uses a gating mechanism to achieve forgetting and updating of information. The forget gate controls the degree of information retention from the previous time step, the input gate determines the addition of current input information, and the output gate regulates the output value at the current time step. Through the hierarchical abstraction of the three-layer structure, the model extracts deep features with temporal discriminative capabilities from the original financial and transaction data.

C. ATTENTION MECHANISM WEIGHTED AND CLASSIFIED OUTPUT

An attention mechanism is introduced based on the temporal features extracted by the LSTM layer to calculate the contribution weight of different time steps to the default prediction result. The attention mechanism uses a learnable weight parameter α to sum the outputs of each time step to form a weighted context vector [13,14].

The introduction of an attention mechanism enables the model to adaptively adjust its focus on historical time points in different prediction tasks. For accounts receivable default risk, corporate repayment behavior often concentrates at specific time points, such as the end of a quarter, the end of a year, or inflection points in an industry cycle . The attention mechanism can effectively capture the impact of these key time points on the risk status. The weighted context vector is concatenated with the output of the last LSTM layer and fed into a fully connected layer for feature fusion. The fully connected layer has 128 neurons and uses ReLU activation. This is followed by an output layer with two neurons, using softmax activation, which outputs the probability distribution of default and non-default.

The model training employed the cross-entropy loss function, with Adam as the optimizer, a learning rate of 0.001, a batch size of 64, and 150 iterations. An early stopping mechanism was used during training: training was halted when the validation set loss stopped decreasing for 10 consecutive iterations to prevent overfitting. Model building and training were completed using the TensorFlow framework, with NVIDIA Tesla T4 GPUs used for accelerated computation.

IV. RESULTS AND DISCUSSION

A. MODEL PERFORMANCE COMPARISON ANALYSIS

To verify the effectiveness of the LSTM combined with attention mechanism model, multiple comparison models were set up for performance evaluation, including a logistic regression model, a traditional LSTM model, and state-of-the-art architectures such as the Temporal Convolutional Network (TCN) and the Transformer model. The results indicate that while the Transformer achieves high global attention, the LSTM+Attention framework provides superior performance in this specific 12-month window due to its optimized handling of sequential dependencies in smaller corporate datasets. Evaluation metrics included accuracy, precision, recall, F1 score, and AUC. The results are shown in Table 1:

TABLE 1. Performance comparison of different models on the test set

Model	Accuracy	Precision	Recall rate	F1 score	AUC value
Logistic Regression	0.786	0.723	0.651	0.685	0.742
Traditional LSTM	0.843	0.812	0.791	0.801	0.874
LSTM + Attention Mechanism	0.892	0.883	0.874	0.878	0.921

As can be seen in Table 1, the performance of the logistic regression model was the worst in all metrics, mostly because of its inability to reflect nonlinear dynamic changes in time series data. The improvement of 7.3 percentage points in accuracy and 21.5 percentage points in recall compared to logistic regression of the traditional LSTM model, by extracting temporal feature, can manifest that temporal information plays a good role in the prediction of corporate default. The LSTM model with attention mechanism outperformed the LSTM model, with 5.8 percentage points improvement in accuracy and 10.5 percentage points improvement in recall. Comparing the values of the area under the curve of the performance metrics, the LSTM model coupled with the attention mechanism yielded 0.921 which showed a high level of ability to indicate the defaulted and non-defaulted samples. The value of the AUC, as a measure of the ranking ability of a classifier, does not depend on the chosen classification threshold, but it is a much more comprehensive indicator of the discriminative power of the underlying model. An AUC value of 0.921 means the model, when randomly choosing a pair of defaulted and non-defaulted samples, has a 92.1%-level probability of correctly ranking the defaulted sample's risk score higher, a level that an application has been shown to have strong value in a positive real-world business application. The future risk implication of the results is that the attention mechanism in the form of weighting and focusing on key time points can help to improve model ability to identify default risk events.

The performance improvements of attention mechanism are reflected mainly in two aspects. First, the attention mechanism is able to adaptively assign weights to different time steps, so that the model pays attention to those time points which are most important for default judgment when processing the input sequence. In the course of business operations, some specific time points, for example, period of signing of the major contracts, the quarterly period of cash collection, receipt of external financing have a decisive impact on the short-term solvency of the company.

Changes in financial data at these time points frequently contain strong default signals. Traditional LSTM treats all the information from the time steps equally, so it is hard to emphasize the importance of these important time points. However, the attention mechanism allocates higher weights to some time points by computing the correlation score of each time step to the prediction target, which means that the model can rely more on these information in making default judgments. Second, the attention mechanism is helpful to increase the interpretability of the model. By outputting the distribution of the attention weights the time interval and feature dimensions on which the model is basing its judgements can be intuitively observed. This transparency is of very high significance for application scenarios like credit risk assessment that have high interpretability requirements.

B. FEATURE IMPORTANCE ANALYSIS

The importance of different feature dimensions in default prediction is analyzed by examining the weight distribution output by the attention mechanism. The weight values output by the attention layer in the model are summarized by feature dimension, and the average attention weight of each feature across all test samples is calculated. A higher weight indicates a greater influence of that feature on default judgment. (See Figure 1.)

The weight of the proportion of accounts receivable overdue for more than 90 days was the largest among all features: 0.134, which suggests that early-stage aging accumulation is the most significant leading indicator for eventual long-term default. This result is consistent with practical experience in corporate accounts receivables risk management; accounts receivables that are more than 90 days overdue typically suggest that the debtor has had a lengthy delay in payment and the difficulty of collecting a payment to a debtor will be significantly greater, with the probability of bad debts being higher. From the standpoint of risk transmission mechanisms, the depreciation of the accounts receivable aging structure can directly cause the decline in the available cash flow in the company, and then affect the repayment ability of the company's own debt, which forms a positive effect of re-inflation. The model starts to put the maximum weight on this feature, which means that they have learned this important risk signal well.

Accounts receivables turnovers came in second place with an average attention weight of 0.112. Accounts receivable turnover is a measure of how well a company is turning its accounts receivable into cash and an important measure of its efficiency. The decrease of the turnover implies a longer time from sales until it is collected, an increase of the capital costs and an increase of the liquidity risk. In the formation of default risk, continuous deterioration of accounts receivables turnover, is often an advance indicator of a accumulation of risk. The fact that the model was able to capture this dynamic change and to use it as important criteria in determining judgment shows it was able to learn the risk evolution process.

The debt to equity ratio is the third by the average attention weight of 0.098. The debt-to-equity ratio is one of the fundamental indicators to measure the overall level of leverage for a company, showing the ratio of a company's total assets financed via debt. A higher debt-to-equity ratio indicates that the company has a greater financial leverage, more pressure to pay its debt, and is more likely to go into default in case of any change in external environment or a decline in operating conditions. The concentrator on this characteristic by the model shows the accurate conception of the relationship between the capital structure of a company and the solvency.

The cash flow ratio is the fourth most important ratio with an average attention weight of 0.087. The cash flow ratio is the relation between the company's net cash flow due to the ordinary course operations and current liabilities and is a direct measure of short-term solvency. Unlike the debt-to-equity ratio, which is focused on the long-term solvency of the company, the cash flow ratio is more focused on whether a company has enough cash flow to pay maturing debts in the current period. In the analysis of accounts receivable default risk, a worsening of the cash flow ratio frequently is a direct precursor to impending default, so the high weighting of it in the model is entirely appropriate. The interest coverage ratio stands in the fifth position and has an average attention weight of 0.076. This indicator is a measure of the relationship between a company's earnings before interest and taxes (EBIT) and interest expenses as a measure of the company's ability to pay interest from operating income. For companies with high levels of debt, a reduction in the interest coverage ratio indicates that the profit margins of company are compressed, its power of paying its debts is reduced, and the risk of default is increased. The weights of sales revenue growth rate, current ratio and index of industry prosperity fall in order but all of them contribute positively to the output of the model. The sales revenue growth rate shows the growth potential of the company, the current ratio is a traditional measure of short-term solvency, and the industry prosperity index is the external macroeconomic environment. The comprehensive distribution of the feature weights is consistent with the basic judgment of the theory of credit risk distribution of factors affecting default, that is, the micro-financial indicators are the fundamental factor for judgment on default, and the external environment factors play a supporting role in judging credit risk, and the feature importance learned by the deep learning model has economic rationality and business interpretation.

C. ANALYSIS OF PREDICTION EFFECTS AT DIFFERENT TIME POINTS

To further explore the role of the attention mechanism in the time dimension, different time windows were selected to analyze the model's prediction performance across different time periods. The test set was divided into four quarterly intervals according to time, and the accuracy and recall

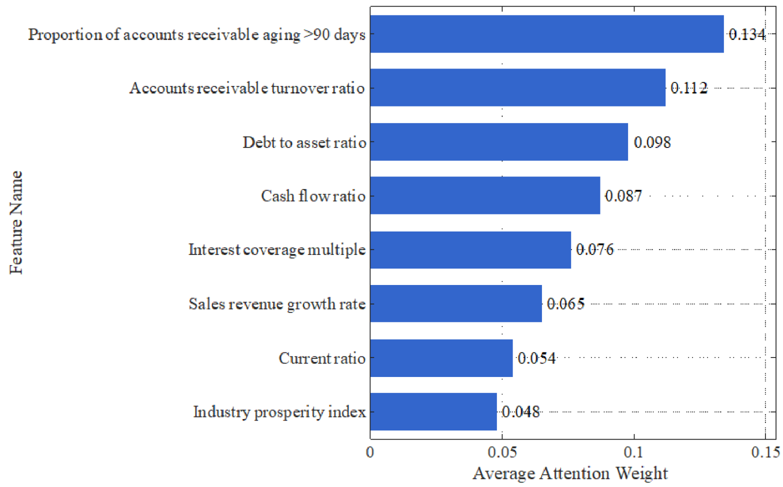

FIGURE 1. Ranking by average attention weight across feature dimensions

of the model predictions were calculated for each interval. The stability of the model's performance under different economic environments and business cycles was analyzed. The results are shown in Table 2:

TABLE 2. Comparison of Model Prediction Performance in Different Time Intervals

Time range	Sample size	Accuracy	Recall rate	Average Attention Span (Months)
First quarter of 2023	178	0.876	0.859	August-November
Second quarter of 2023	184	0.889	0.871	September to December
Third quarter of 2023	176	0.901	0.883	July to October
Fourth quarter of 2023	174	0.894	0.876	August to December

As presented in Table 2, the model's accuracy and recall were at the high level in all the quarters and became oscillated between 0.876 to 0.901 and 0.859 to 0.883 for accuracy and recall, respectively. This stable performance indicates that the model had good generalization ability in different periods of time, and the prediction performance did not significantly decrease in a certain period, so it verifies the robustness of the LSTM+attention mechanism model in time series prediction.

The third quarter had the best forecasting performance with an accuracy of 0.901 with a recall of 0.883, which is the best of the 4 quarters. This phenomenon one can understand from the point of view of business cycle. The third quarter usually corresponds to July to September, an important period for the settlement of companies to make business plans for the second half of the year. Companies often adjust inventory, collect accounts receivable and allocate funds during this stage, making the financial information during this stage more volatile, so there's a possibility that default signals would appear in the financial indicators. At the same time, the third quarter is also a big time for upstream and downstream companies in the supply chain to negotiate about payment terms and make arrangements on funding. Changes in structure and quality of accounts receivables during this time have a stronger indicative effect on subsequent default risks. The great performance of the model in the third quarter indicates that the model successfully captures such cyclic risk signals.

Statistical data on average attention concentration periods shows that attention weights are primarily concentrated in the period of July and December, i.e. the most recent 3-5 months of the 12-month input window. While the LSTM layers maintain the integrity of the long-term 12-month dependency to understand the firm's trajectory, the attention mechanism selectively highlights these specific recent months as the 'trigger period' for default. This confirms that while the model captures long-term patterns, the final risk transition is often catalyzed by high-weight recent volatility. In the formation of the risk of the default of corporate credit, the recent financial performance and trading behavior often are more direct signals, while the earlier information, although to some extent has some meaning on understanding the long-term operating status of a company, generally have relatively little predictive value in the study of short-term default risk. The mechanism of attention can automatically learn this pattern, giving more weight to the recent time steps, thus making the model more sensitive to the contemporary state of the risk.

It's worth noting the periods of the year that we focus most on attention are different for each quarter. In the second and fourth quarter of 2023 there was a peak attention period in the 12th month in the time window, while in the first and third quarters there were more concentrated peak attention periods in the second half of the time window. This difference may be related to the different business rhythms of companies in different quarters; the end of the quarter is often a critical point in companies conducting financial accounting and collecting accounts receivable, so quarter-end information may have a larger influence on predicting how well companies are likely to do.

Further analysis on the distribution of attention weights over time, we can also see that there are significant differences on their distribution in dealing with prediction tasks for different companies. For relatively stable functioning companies, the model tends to focus attention fairly equally on several time steps, styling thus judgments on long-term trends. However, for those companies that have volatile operations or other recently significant changes, the model gives a lot of attention to recent time steps, particularly those points where financial indicators have changed significantly. This adaptive adjustment capability is the most fundamental advantage of the attention mechanism over the fixed weight method, and the model achieves better predictive performance on different types of company samples.

Analysis of the errors of the model prediction shows that misjudgment is mainly made in two types of samples. The first type is the companies that are in the brink of default and their financial indicators are similar to that of normal companies, so it is difficult to accurately differentiate those models. The second is sudden defaults by external shocks; these companies do not have a clear trend of poor financial indicators before going into default and a lot of historical signals for the model to use in making judgments. To deal with such situations, future research could consider incorporating more diverse data, for example supply chain relationship network data and information of change in macroeconomic policies to further improve the ability of the model to find out marginal samples and identify sudden events.

V. CONCLUSION

This study focuses on dynamical assessment solutions of accounts receivables risk of default by building a deep learning model equipped with a Long Short-Term Memory network (LSTM) and attention mechanism. By modeling 72 consecutive months of financial and transaction data of 2844 companies, the model can successfully extract the temporal features and make contributions of key time points on the default risk. Experimental results indicate that the LSTM-attention mechanism model has better performance than the logistic regression model and the traditional LSTM model in terms of accuracy, recall, F1 score, and AUC, and fully demonstrates that the dynamic judgment of corporate default risk is closely related to time information and the attention mechanism. The results of feature importance study show that the structure of aging and the efficiency of capital turnover are a core indicator to determine the default risk, while the distribution of the attention weight reveals the major influence that recent historical data has on the prediction results. This study proposes a feasible technical method for evaluating corporate accounts receivable default risk, which has practical value on applying the research into credit management of financial institutions and enterprises. Future research could further utilize corporate supply chain relationship network data and macroeconomic policy variables, in order to further expand the model input dimensions, and explore whether it is possible to combine graph neural networks and time series models to further improve the comprehensiveness and accuracy of risk prediction.

AUTHOR CONTRIBUTIONS

Conceptualization –Yiqing Huang and Daoping Huang; methodology – Yiqing Huang and Daoping Huang; investigation – Yiqing Huang and Daoping Huang; writing-original draft preparation – Yiqing Huang and Daoping Huang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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