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Deep Learning and Metaheuristic Approaches for Financial Risk Prediction in Digital Economy

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Abstract:

Predicting financial risk has become increasingly important as digital-economy firms generate highly volatile and complex data. Existing Deep-Learning (DL) models struggle with high-dimensional inputs, unstable optimization, and limited generalization. To address these issues, this study proposes a hybrid framework combining Quantum-controlled Long Short-Term Memory (Q-LSTM) networks with a Multi-Objective Artificial Bee Colony optimizer (MOABC). Using quarterly data from twelve Chinese e-commerce firms (2012–2022), the model optimizes learning rate and hidden-layer configuration after reducing 14 financial indicators to 5 latent factors via factor analysis. Experimental results show that MOABC-QLSTM achieves superior accuracy, with a Mean Squared Error (MSE) of 0.0067, a Mean Absolute Percentage Error (MAPE) of 3.88%, and an R^2 of 99.78%. It outperforms Particle Swarm Optimization (PSO), Differential Evolution (DE), and Genetic Algorithm (GA) tuning, LSTM models, and other state-of-the-art approaches. The findings demonstrate that integrating quantum-inspired temporal modelling with swarm-based multi-objective optimization provides a stable and effective early warning system, supporting regulators, auditors, and financial institutions in risk monitoring within the digital economy.

Keywords: Financial risk prediction, deep learning, digital economy, meta-heuristic approach, LSTM, quantum, artificial bee colony, parameter tuning.

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1. Introduction

The conventional financial sector quickly integrates with the most recent cutting-edge Internet technology. With the influence of ideas like “Internet+” and “Digital Economy,” it is constantly being divided. Among them, Digital finance for consumers has experienced significant growth over the previous few years and has a variety of market prospects based on actual usage scenarios (Qi et al., 2020). The contribution of online finance platforms to the economy’s growth is obvious. Still, the turmoil in the online lending sector harms investors and undermines the stability of the real economy and the financial market. Numerous factors can exacerbate the risk of platform problems. These may include internal factors such as financial difficulties, fraud, mismanagement of risk control, and self-financing, as well as external factors such as an unstable regulatory environment, a lack of a credit system, macroeconomic downturns, and industrial downturns (Zhou et al., 2019).

E-commerce is currently a significant driver of economic growth in nations and regions. Since the COVID-19 pandemic began, many businesses have rapidly entered the E-commerce space and revolutionized their business methods. This has changed people’s old ways of living, sped up economic connections, and increased our access to a wide range of goods and services. As a result, businesses can fully operate e-commerce, modernize and transform outdated management and business methods through information technology, and stay ahead of the curve to avoid being eliminated (Simjanović et al., 2022).

However, analyzing corporate financial data is exceedingly challenging due to its vast, diverse volume and ongoing changes (Gao, 2022). Due to their strong ability to handle nonlinear mapping challenges, Artificial Neural Networks (ANNs) are widely used in big data and machine learning (Pouyanfar et al., 2018). To provide efficient analysis results, the financial risk model in the ANN is a machine learning model that can perform both testing and training on high-dimensional financial data. To develop more useful financial risk prediction models, numerous academics from domestic and international universities have recently undertaken detailed studies of financial risk using machine learning (Huang et al., 2020; Zhu et al., 2022).

To address issues with Depth of Market (DOM) prediction, Kamaran et al. (2020) developed a hybrid model based on a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network and the Convolutional Neural Network (CNN) attention mechanism. The accuracy of the final estimation was 87%. Jang et al. (2020) incorporated special pointers from the construction business into an LSTM-based model to forecast a construction contractor's performance over the next 3 years. With a 94.21% accuracy, Ling and Cai (2022) presented a financial risk-based warning system centered on the Wolf's Pack-based optimization (WP) algorithm and LSTM. With an estimated accuracy of more than 96.01% for market analysis. Lei and Li (2022) developed an early warning system for market risk using the Whale Optimization Algorithm (WOA) and LSTM. A financial risk management-optimized Deep Learning (DL) framework was developed by Chen and Long (2023). The intelligent swarm optimization algorithm uses the Mean Squared Error (MSE) and predicted values from the Long Short-Term Memory (LSTM) neural network as the fitness function. The Particle Swarm Optimization (PSO) algorithm is then applied to optimize the learning Range value (LR) and the LSTM neural network's neuron count. According to the previously cited study, the LSTM neural network is well-suited to handle and forecast time-series data, particularly that closely resembles financial data. But as of right now, no broadly applicable model exists that can reliably forecast corporate financial problems. This paper's primary contribution is as follows:

This study developed an intelligent system that predicts financial risk using Quantum LSTM characteristics, suitable for analyzing financial time-series data.

First, the original financial public factors are analyzed using factor analysis to avoid overfitting.

The second is the multi-objective Artificial Bee Colony (ABC), a meta-heuristic-based optimization algorithm that is suggested for fine-tuning the Q-LSTM's hidden layers and learning rate. Third, the proposed MOABC-QLSTM is evaluated using various indices and compared with conventional meta-heuristic algorithms. Compared with the baseline, the proposed model achieved higher accuracy and lower error rates in financial risk prediction, enabling more informed business decisions.

This article is formatted as follows. The literature on the forecast of financial trouble is covered in Section II. Section 3 introduces and clarifies the model under discussion. In Section 4, the prediction performance of each selected deep model is analyzed, optimized, compared, and summarized. Section 5 concludes with suggestions for future improvements.

2. Related Work

The relevant literature is covered in this section. on financial risk prediction systems. Wu et al. (2022) offers a stock market forecasting model that combines the classic Altman Z-Score model with a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN). The paper's contribution is the introduction of a novel hybrid business crisis warning model that combines an MLP-ANN and a Z-score model. The novel hybrid default forecasting model is illustrated using Chinese data. The hybrid neural network model's average correct classification rate is 99.40% based on empirical investigation. Zhao et al. (2024) incorporate several deep learning methods, including transfer learning, Back Propagation based Neural Network (BPNN), and Bi-LSTM, to improve the efficiency and accuracy of financial risk prediction models and the risk warning system. The outcomes show that the suggested algorithm outperforms the baseline methods across various valuation models. For example, accuracy on the Altman's Z-Score dataset has improved by 1.4%.

Dexiang et al. (2023) suggest combining these two ideas in a novel way to produce a Deep Learning + Elliott Wave Principle (DL-EWP) model. This model uses financial data series to extract and categorize Elliott Wave Patterns to anticipate future market movements. Applying the model to financial data from three major markets empirically proves its efficacy. Elhoseny et al. (2022) developed a new prediction model for financial distress using the Adaptive Whale Optimization with Deep Learning (AWOA-DL) approach. The AWOA-DL method seeks to determine whether a business is facing financial trouble. The AWOA-DL technique uses a Deep Neural Network (DNN) model, a multilayer perceptron for prediction, and AWOA-based hyperparameter tuning processes. The DNN model's main function is to forecast financial distress by using financial data as input. Furthermore, the model's hyperparameters are adjusted using AWOA, thereby improving predictive performance. Hybrid deep learning architectures combined with evolutionary optimization have demonstrated strong capabilities for predicting corporate financial distress (Rahman et al., 2024). Recent studies show that quantum-inspired neural sequence models significantly improve nonlinear financial time-series forecasting performance (Zhou et al., 2024). Advancements in multi-objective swarm intelligence have proven effective in complex financial forecasting and risk analytics tasks (Gupta and Li, 2025).

Gu (2023) explains how to create an accurate risk prediction, Optimization-Based Rule Pruning for Bayesian Neural Networks (ORP-BNN), using a backpropagation-assisted neural network for pre-validation of both new and imbalanced data in the current financial context. The risk estimation model is designed to support minimal-risk financial management and business requirements. This is intended to be a linear model of snowfall, in which the BNN determines the importance of funding allocation and constraints. The snowfall model heavily depends on allocation or restraint, which is achieved by assigning required weights based on the results of prior financial decisions. The computational model's gradient loss functions calculate the weight factor. Several structural alterations that have been used in the past for effective financial management are incorporated into the training process.

Liu et al. (2021) outlined the need for and the path to a new, big-data-driven machine-learning approach to credit risk control. To theoretically support the empirical analysis that follows, we first introduce the fundamental algorithmic principles of machine learning. From there, we explain why we chose a particular machine learning technique and develop a model of an Internet-based consumer finance credit risk control strategy based on machine learning. Second, we use test data from the Internet Consumer Finance S company as our sample and conduct an empirical analysis using a machine-learning-based credit risk control model for internet consumer finance. Ma (2023) quantitatively assesses the financial risks across various fields to identify the major industries and regions with the highest financial risk distribution. This work aims to improve risk monitoring and analysis, act quickly to identify risks using tools like situation reports, and risk warning letters to prevent their spread, and perform well in risk prevention and response. Effectively identifying regional financial risks, quickly grasping the distribution and effects of different risks, and performing well in risk monitoring and prompting are all necessary. DL continues to play a central role in financial risk modeling within rapidly evolving digital-economy environments (Huang et al., 2025).

The mechanism of financial systemic risk is examined by Sun and Li (2022). After that, the index system for early warning and financial security assessment was rebuilt using deep learning technology for the first time in the world of financial investments. DL technology is used to detect systemic financial issues early on. This makes empirical research possible and provides regulatory bodies with a solid foundation for constructing a financial risk early warning system. The first section of the study by Chen and Cai (2022) examines three aspects of digital change and business growth: the method by which digital change affects enterprise growth and the variety of its effects. This article also develops a financial early-warning model based on convolutional neural networks to support firms digital transformation efforts.

Using a back-propagation neural network, Song et al. (2023) constructed an early warning model for financial risk. To do this, the People's Republic of China's 136 listed Internet financial companies financial data from 2010 to 2019 was chosen as the sample for the empirical test. We used the K-means clustering algorithm to classify the financial situation of businesses as either "healthy" or "early warning." In addition, seven common characteristics were identified through factor analysis, which helped construct the early warning model. Overall, we verified the model's exceptional prediction efficiency and complete accuracy. As a result, the model created through simulation and training with the back propagation neural network method can identify businesses with hidden financial situations and won't mistakenly identify businesses in good financial standing. Liu et al. (2021) propose a novel, big-data-driven machine learning approach to credit risk management. To theoretically support the following empirical analysis, we first introduce the fundamental algorithmic principles of machine learning. From there, we explain why we chose particular machine learning models and develop a machine learning-based consumer credit risk control strategy. Second, we use the Finance S company's test data as the sample data and conduct a study analysis of the Consumer in internet Finance risk control for a credit strategy model based on machine learning. This comparison of training results shows that machine learning algorithms are good at identifying the main reasons credit customers don't pay on time.

Fig. 1 provides an overview of the developed financial risk prediction system on the digital economy platform using the proposed meta-heuristic-based DL approach. The first step was to collect data and enter it into the publicly accessible China Stock Market and Accounting Research (CSMAR) database. Several data pre-processing procedures, including screening, were then employed to build the digital enterprise indication system. To eliminate the influence of differing indicator magnitudes on the model, Z-score normalization of the filtered data was performed. To reduce the risk of model overfitting, the indicator system is converted from 14 correlated indicators to 5 independent common factors in the second stage after factor analysis. The third stage involves converting the data into a matrix format that the Q-LSTM neural networks can use as input and extracting the common factor characteristics from the data. The fundamental network structure of the model is optimized during training using MOABC. In this, the learning rate and the number of neurons in the hidden layer are adjusted to further improve the model's predictive accuracy. The fourth stage involves predicting the test set using the trained data. The performance of the proposed MOABC-QLSTM model is then evaluated by comparing its predictions with those of the benchmark model using the same evaluation criteria.

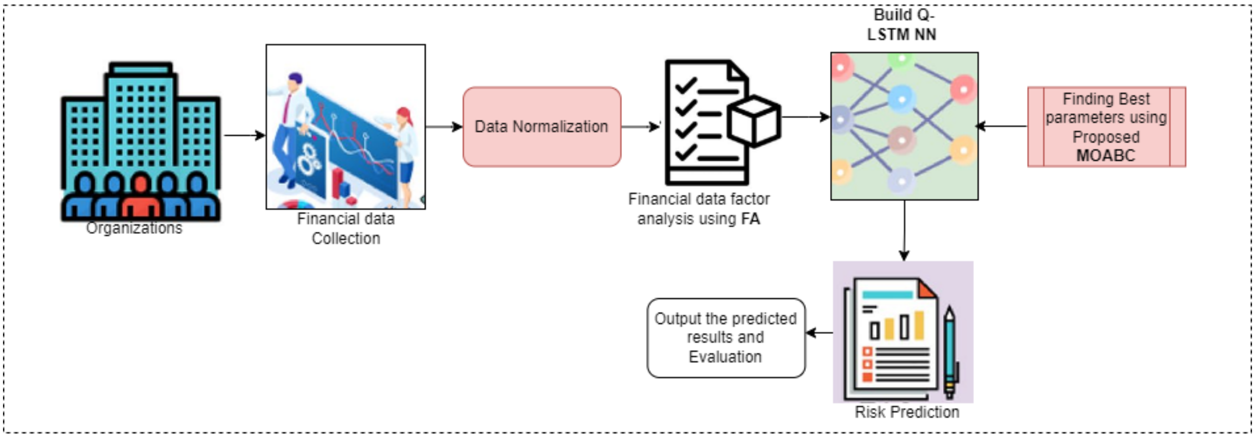


Fig. 1. Overview of proposed financial risk prediction system

3.1. Data Sources

The financial information of twelve listed E-commerce enterprises from 2012 to 2022 served as the research object for this study. Except for some missing numbers that had to be manually entered from the Wind database, all information came from the CSMAR database. As shown in Table 1, the pre-selected indicators for this paper are 13 financial indicators (cash flow, operating, development, and profitability) and 1 non-financial basis indicator (registered capital), which can more fully reflect the enterprise's financial status. These are based on studies of early warning systems for financial risk conducted by most domestic and international scholars (He et al., 2022; Wang, 2022).

Table 1. Financial indicators

Symbols	Indicators	Variable type
X1	Debt_Asset_Ratio	Dependent Variable
X2	Current_Ratio	
X3	Quick_Ratio	
X4	Cash to Current_Ratio	
X5	Receivables Turnover_Ratio	
X6	Current Asset_Turnover_Ratio	
X7	Total Asset_Turnover_Ratio	Independent variable
X8	Assets_return	
X9	Rate_of_retuns on stockholders_Equity	
X10	Operation_Cash_into_Asset	
X11	Grow_Ratio of total assets	
X12	Growth Rate_of_owners_equity	
X13	Net_Cash_Flow	
X14	Registered_capital	

3.2. Data Preprocessing

For the chosen samples, several data preprocessing procedures, including screening and imputing missing values, are necessary to ensure the authenticity of the study data. To eliminate unit constraints, convert the least into dimensionless purity values, and to eliminate the effect of different magnitudes on the model, the financial data must be normalized. The study finds that the Z-score standardization technique is more appropriate for data normalization than minimum and maximum normalization, as it preserves more final feature information, according to Singh and Singh (2020). Thus, the Z-score method is applied in this work, along with its formula for Eq. (1), as follows:

$$Z^* = \frac{Z - \mu}{\sigma} \tag{1}$$

Where, μ declares each column mean value of the indicators and σ denotes the group of each column standard deviation of the indicators.

3.2.1. Factor investigation

A multivariate statistical technique called factor analysis can be used to transform a large number of potentially interrelated variables into a set of uncorrelated composite indicators. By examining the internal dependencies among more variables and using a few fake/dummy variables to represent their basic data structure, it explores the structure of the observed data. Factors, often referred to as "fake" or "dummy" variables, are unobservable latent variables (Shrestha, 2021).

If p, the correlation of variables is random, and the variables include m factors that are independent of each other, then factor analysis is represented by Eq. (2-4).

$$X_1 = a_{11}F_1 + a_{12}F_2 + \ldots + a_{1n}F_n + \varepsilon_1 \tag{2}$$

$$X_2 = a_{21}F_1 + a_{22}F_2 + \ldots + a_{2n}F_n + \varepsilon_2 \tag{3}$$

$$X_p = a_{p1}F_1 + a_{p2}F_2 + \ldots + a_{pn}F_n + \varepsilon_1 \tag{4}$$

Where, F1, F2 … Fn are the common factors, and its coefficients are the factor loadings, ε is the special factor which is not added to the common factors.

To identify the common factors influencing the variables, factor analysis first recombines the information from the original variables rather than trading them off. This simplifies the data and prevents overfitting. Then, factor analysis can increase the interpretability of the factor variables by rotating and clearly labeling them. Factor analysis will be used in this article to simplify quarterly financial data indicators for e-commerce companies. This study first determines whether factor analysis can be performed by running Bartlett's test and the Kaiser-Meyer-Olkin measure (KMO). Factor analysis should aim for a KMO value of 0.9, while values between 0.7 and 0.9 are acceptable, 0.61 and 0.70 are preferred, 0.50 and 0.60 are acceptable, and values lower than 0.5 ought to be avoided. Applying the spherical test of Bartlett's to determine the correlation between each variable in the unitary matrix-based correlation matrix. If Sig < 0.001, the idea of a null hypothesis is rejected, indicating that the variables are correlated and amenable to factor analysis. On the other hand, if the null hypothesis is not rejected, it suggests that the variables can provide information on their own and are not appropriate for factor analysis. This paper identifies the first five most common factors based on 15 indicators, as Chen and Long (2023) show that these factors possess characteristic roots exceeding 1 and a variable-explained contribution rate of 82.732%. These results demonstrate the strong representativeness of the first five common factors.

If n common Factors are found, the common factor "i" can be seen as a specific component because the loading of factors coefficients for "a", "b", "c", and "d" are bigger. Therefore, the X2, X3 and X4, all of which show liquidity that make up Factor 1 in this work. Operating capacity is shown by the X5, X6, and X7 that make up Factor 2. The X12and the X11, which demonstrate development capability, make up Factor 3. X10 and X13 from operation-based activities per share, which show the flow capacity of cash, make up Factor 4. Factor 5 is based on X8 and X9, which indicate profitability.

After dimensionality reduction, the financial data, obtained by analyzing all factors, follow a normal distribution over [−15, 10]. This reduces the risk of model overfitting, enabling the Q-LSTM neural network to better analyze time series data and improve prediction accuracy. Following factor analysis, the samples were transformed from 14 correlated indicators to 5 common, uncorrelated factors. These factors will serve as input data for the Q-LSTM neural network model used in the following experiments.

3.3. Quantum LSTM-Based Financial Risk Prediction

Quantum-state evolution explains quantum-based evolution from one state to another. Applying quantum gates converts states from quantum to density matrices in the context of quantum computing theory, using unitary matrices whose dimensions correspond to the quantum bit count (n=2^m) of the gate. In this study, complex-valued data is employed within Q-LSTM networks to model and replicate the behavior of quantum systems. The evolutionary modules are set up with inputs and outputs that comply with n×n. Thus, the quantum system's initial dimensionality does not change within the sentence after feature learning.

The fully connected layer, also known as the complex-value linear layer, is the central component in a complex-valued neural network. In this layer, each neuron forms connections with all neurons in the preceding layer, creating a densely interconnected network. The following Eq. (5) is a description of the computing process:

$$F = wX + b \tag{5}$$

The weight matrix w represents the connection strengths between neurons, while b denotes the bias term that shifts the output of the network's layer. A PyTorch library-based version of the complex data linear layer was presented by Trabelsi et al. (2017). This layer employs two separate linear layers, each processing the real and imaginary parts independently. It uses the concepts of complex-valued computation to determine the most recent real and imaginary components. Eq. (6-9) shows the particular computation process:

$$F_r\left(X\right) = w_r X + b_r \tag{6}$$

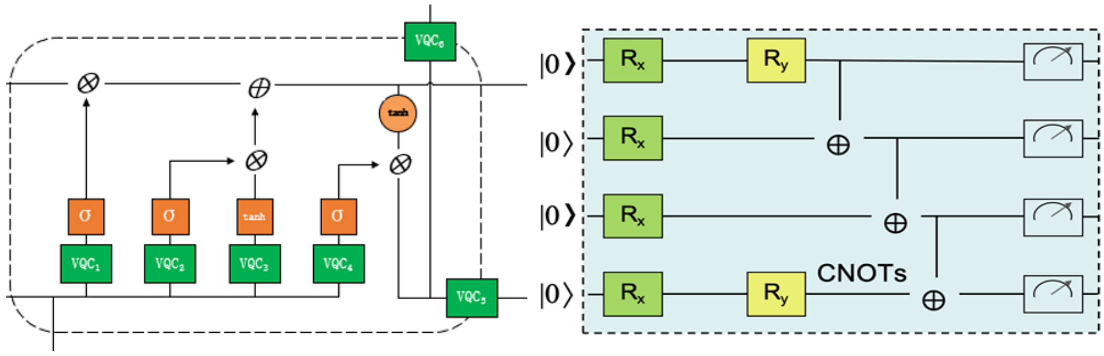
$$F_i\left(X\right) = w_i X + b_i \tag{7}$$

$$F_c\left(X\right) = F_r\left(X\right) - F_i\left(X\right) + i*\left[F_r\left(X\right) - F_i\left(X\right)\right] \tag{8}$$

$$= w_r X_r - w_i X_i + b_r - b_i + i*\left[w_r X_i + w_i X_r + b_r + b_i\right] \tag{9}$$

Where i denotes the imaginary part.

The Q-LSTM model enhances the traditional LSTM framework by replacing the conventional neural network units with Variational Quantum Classifiers (VqCs), thereby incorporating quantum computational capabilities into the memory cells. Quantum circuits, or VqCs, are outfitted with quantum characteristics that enable them to withstand the intrinsic noise that comes with quantum computing. Classical gradient descent can be used to optimize these parameters iteratively (Griol-Barres et al., 2021). The VqC performs both data compression and feature extraction. A diagrammatic summary of the Q-LSTM design is presented in Fig. 2a, while Fig. 2b displays the VqC parts that are utilized in the Q-LSTM. The three components of the VqC are a quantum measurement, a variational layer with stratification, and data encoding. The complex-valued linear layer's output is transformed into quantum-based states by the data encoding layer. The gradient descent algorithm is used by the layer with variation to update the circuit's parameters.



(a) (b)

Fig. 2. (a) Q-LSTM structure (b) VqC components

One of the two Q-LSTMs that make up the proposed Q-LSTM is the virtual portion. The final eigenvector is obtained by linearly combining the findings, and it is then fed to the measuring function. Our Q-LSTM model uses a two-layer quantum circuit, with each VqC containing four quantum bits. It employs a word embedding size of 64 and sets the vocabulary size as the output dimension to satisfy the model's requirements. The mathematical construction for the Q-LSTM is given in the following Eq.'s (10-16).

$$F_t = \sigma\left(VqC_1\left(V_t\right)\right) \tag{10}$$

$$I_t = \sigma\left(VqC_2\left(V_t\right)\right) \tag{11}$$

$$\tilde{C} = tanh(VqC_3\left(V_t\right)) \tag{12}$$

$$C_t = F_t * C_{t-1} + I_t * \tilde{C} \tag{13}$$

$$O_t = \sigma(VqC_4\left(V_t\right)) \tag{14}$$

$$H_t = VqC_5\left(O_t * \tanh\left(C_t\right)\right) \tag{15}$$

$$Y_t = VqC_6\left(O_t * \tanh\left(C_t\right)\right) \tag{16}$$

This study employs the quantum-computing-based measurement to forecast the model's output. The measurement module predicts the classification outcome using the high-level features it collected from earlier modules as input. The number of classification labels and the number of measurement base vectors are in agreement. To obtain the final classification result, we select the class with the highest expected value (Lai et al., 2023). Furthermore, since the result measurement is a real number, we extract each label with a probability value to make a prediction vector. This vector is then concatenated with other model's prediction findings, promoting a combined model fusion strategy that improves experimental results.

3.4. MH-Based Optimization called MOABC for Q-LSTM

The system's predictive effectiveness is enhanced through parameter tuning using a meta-heuristic approach called MOABC. Karaboga (2005) developed the swarm optimization method known as ABC based on the social behavior of honeybees. It consists of two parts, like worker and unemployed bees. The food source will be found by worker bees, who will also document food quality information and share it with others. Unemployed bees fall into two categories: those that select the superior food source after becoming aware of it, and those that are only bystanders. Scout bees, however, will look for a new food source when the one they are currently using runs out (Karaboga, 2010). In this investigation, the ABC selects the assault-detection aspects that perform best. The actions to take are as follows:

Step 1: To start the bee swarm, the vector's components with features are placed at various points within the vector. Whether an attribute's vector value at that point is 1 determines whether it is accepted or rejected. Using Eq. (17), we calculate the bee initialization.

$$X_m = L_i + r\left(0,1\right) * \left(U_i - L_i\right) \tag{17}$$

Where food source is X_m, the upper and lower level solution U and L are space respectively, r is the number in random where $r \in [0,1]$.

Step 2: The worker bee computes its exploration of its neighbor in search of food using Eq. (18).

$$V_{m_i} = X_{m_i} + \varphi_{m_i}\left(X_{m_i} - X_{k_i}\right) \tag{18}$$

Where 'i' is random parameter, the randomly selected food source X_k, φ is the range -1 to 1 in random. After exploration V, each feature fitness is computed using Eq. (19)

$$F_i = \begin{cases} \dfrac{1}{f_i + 1} \; if \; f_i \geq 0 \\ 1 + |f_i| ? \, if \; f_i < 0 \end{cases} \tag{19}$$

Where f_i is the solution of ith number with objective value.

Step 3: After locating the food supply, the worker bee notifies the other bees of its location and quality. Eq. (20) illustrates the likelihood that the observer bee will choose a food source.

$$P_i = \frac{F_i}{\sum_{i=1}^{N} F_i} \tag{20}$$

Where food source F_i represents the ith fitness solution, and N is the total food sources.

Step 4: If the effectiveness of its food source is not increased, the scout bee will reject the current solution and use Eq. (17) to randomly search for a new one. Two components are merged to provide ABC for multi-objective optimization, which is comparable to MOPSO (Coello and Lamont, 2004). An archive is responsible for tracking the non-dominated Pareto solutions and serves as the initial component. The leaders who support alpha, beta, and delta solutions in their hunt process are chosen using the second component. The archive, which may hold non-dominated solutions generated by the archive controller, is a basic storage mechanism. When the archive is full or when solutions try to enter the storage, it maintains control. There is a limit to the amount of member storage in the archive. Three scenarios could be followed in the process of seeking solutions. They are defined as follows:

- Any one of the archived residences has a dominant influence over the new member. In this instance, the archive does not contain the solutions.
- The new solutions outweigh the solutions from the archives. In this instance, the new solutions are saved in the archive, and the dominating solutions are removed.
- The newly developed solution is kept in the archive if it does not outperform the archived solution.
- The grid technique is used to reorganize the space's division and steer clear of the most congested solutions if the archive is full. To expand the diversity of the Pareto-optimal front, new solutions are added to the least-packed segment.

The process of eliminating solutions is based on the number of solutions in each segment. When an archive fills up, the solutions in the most densely packed portions are removed first, and then solutions are deleted at random to make room for new ones. The segments are expanded to cover the new solutions as they are inserted outside of them.

In the second part, the top three solutions are identified, and these leaders guide the search agents into the search space to locate the global optimum. Pareto optimality prevents comparison of the solutions in the multi-objective search domain. The leader selection procedure has fixed this issue. As mentioned earlier, one of the non-dominated solutions, namely the alpha, beta, and delta weaves, based on the roulette wheel technique, is used in the leader selection process, which chooses the least crowded area of the search space. The probability of each segment is as follows in Eq. (21):

$$P_i = \frac{g}{NP_i} \tag{21}$$

Where g is the constant number, which is greater than 1, N is the Pareto solution of the ith segment. The parameters of the Q-LSTM after the fine-tuning are: number of LSTM layers is 2, loss function is MSE, Number of hidden layers is 34, optimizer is MOABC, learning rate is 0.0001, and Epoch is 500. MOABC has an $O(mn^2)$ computational complexity, where n is the population's size and m is the number of objectives. The Q-LSTM classifier parameters will be adjusted using MOABC, and the process will be repeated until the optimal number of iterations is reached.

4. Experimental Results Analysis and Comparison

The experiments were carried out with the PyTorch deep learning framework, Python programming, the machine learning library Scikit-learn, and the Anaconda and PyCharm software operating environments (Paszke et al., 2019).

4.1. Evaluation Indices

The strength of the FA-PSO-LSTM-based prediction method is evaluated using five commonly used error assessment metrics (Chicco et al., 2021), which are computed as shown in Table 2 and consist of Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). In this table, $\hat{y}_i$ is the predicted value, y_i is the actual value, N is the total number of data samples. The higher the R2 value, the better the method; the lower the error metrics, the better the model's accuracy.

Table 2. Evaluation indices

Metrics	Equations
R2	$1-\frac{\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)}{\sum_{i=1}^{N}\left(y_i-\overline{y}_i\right)}$
MSE	$\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2$
RMSE	$\left(\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2\right)^{\frac{1}{2}}$
MAE	$\frac{1}{N}\sum_{i=1}^{N}\left\|y_i-\hat{y}_i\right\|$
MAPE	$\frac{100\%}{N}\sum_{i=1}^{N}\left\|\frac{y_i-\hat{y}_i}{y_i}\right\|$

Essential financial indicators can be forecasted to serve as a guide and assess the enterprise's near-term financial status. In this paper, the debt-to-asset ratio is a key corporate finance indicator for the third quarter of 2022. The achievement of monetary indicator prediction is primarily dependent on historical financial data. Fig. 3 illustrates the MOABC-QLSTM prediction for the liability ratio of each asset, with 2 layers fixed. As shown in Fig. 3, the deviation between the predicted and actual results is similar, and the maximum difference occurs for enterprises 4 and 8. Average deviation occurs for No. 2, 3 and 10, and less deviation occurred on the numbers 1, 5, 6, 7, 9, 11, 12 and 13. In this study, the Debt-to-Assets Ratio threshold is set at 0.7, in line with the e-commerce industry's characteristics. Businesses should be aware of their financial situation if the projected Debt-to-Assets Ratio is above 0.7 (Cao et al., 2022).

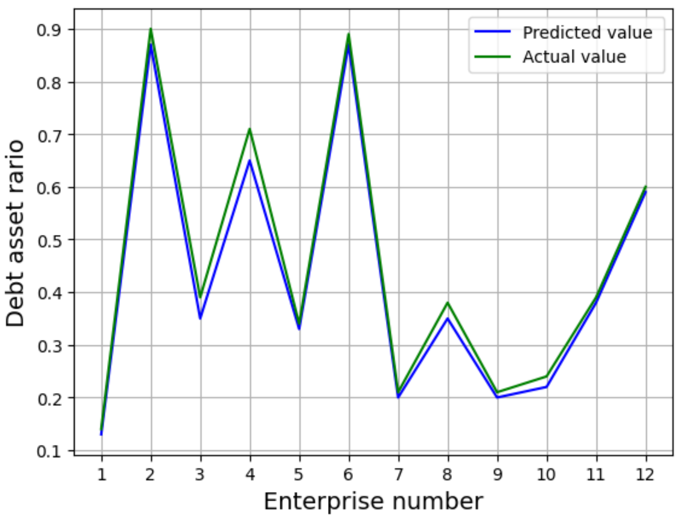


Fig. 3. Predicted results of debt assets ratio (X1 indicator)

4.2. Comparison with the Optimization Approaches

The research findings of numerous academics, both domestically and internationally (Qiu et al., 2020; Suddle and Bashir, 2022), have led to the selection of PSO, DE and GA as intelligent methods for repeatedly optimizing the parameters of Q-LSTM models in this paper. A genetic method is a mathematical representation of biological progress that mimics the genetic mechanisms of Darwinian evolution and natural selection. It is a technique for finding the best answer by imitating the process of natural selection. The Differential Evolutionary Algorithm is a novel approach to evolutionary computing that mimics biological evolution by using a stochastic model to repeatedly iterate and conserve individuals that have adapted to their environment. The MOABC technique is used to optimize the learning rate and the number of hidden-layer neurons, with a maximum of 10 iterations and a weight factor of 0.5. The global optimal solutions for the parameter fine-tuning of the proposed MOABC are shown in Fig. 4. Based on this, the lowest value occurred in the 8th iteration, and the final hidden layer neurons are fixed as 112, and the learning rate is fixed as 0.0001.

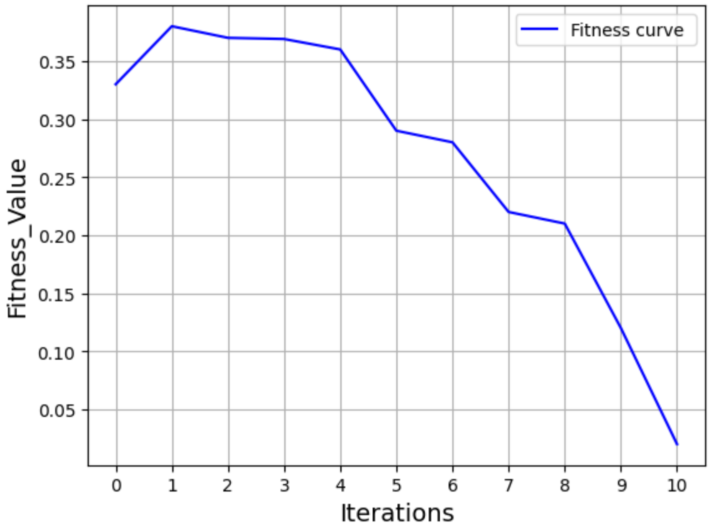


Fig. 4. MOABC adaptability changes based on fitness value

Table 3 displays the optimal results for each intelligent method across the number of hidden-layer neurons and the learning rate. The prediction accuracy of the debt asset ratio after parameter fine-tuning using intelligent approaches with Q-LSTM is shown in Table 3. Based on the results, the proposed MOABC with Q-LSTM has the smallest average prediction error and improved accuracy in predicting financial risk.

Table 3. Optimal value of the parameters with its prediction accuracy

Approaches with QLSTM	No. of hidden layers neurons	Learning rate	Prediction accuracy
PSO	109	0.22	0.964
GA	53	0.058	0.943
DE	169	0.016	0.914
MOABC	112	0.0001	0.989

4.3. Prediction Comparison of Conventional Approaches

The financial risk prediction for the considered data is performed using the proposed MOABC-based optimization with the developed Q-LSTM, along with conventional DL classifiers such as LSTM, RNN, and GRU. Fig. 5 displays the loss variations for each model's predictions on the test dataset and the true values. As evidenced, the suggested MOABC with Q-LSTM reduced the loss after the 50th iteration and remains the same for further analysis. Various other approaches and loss variations occurred after the 100th, 150th and 200th iteration to reach the lower value.

Fig. 6 shows the prediction deviation of each approach for the enterprise gearing ratio for the 2022 3rd quarter. From these illustrations, it is noted that the proposed MOABC-QLSTM has the smallest average error among the predicted and actual value compared to the other models.

The prediction performance of the different approaches is thoroughly assessed using various evaluation metrics, with the results presented in Table 4. In terms of R2, the obtained results of the approaches such as LSTM, MOABC-LSTM, MOABC-RNN, MOABC-GRU, and MOABC-QLSTM (Proposed) are 89.22%, 96.28%, 95.39%, 91.24% and 99.78%, respectively. The higher R2 value supports the better method. Therefore, the proposed system is superior to other approaches. The Mean Squared Error (MSE) value of the suggested approach is 0.0067, which is lower than that of the considered approaches. In terms of MAE, the proposed model yields 0.1082, which is lower than that of the conventional system. In terms of MAPE, the obtained results of the approaches such as LSTM, MOABC-LSTM, MOABC-RNN, MOABC-GRU, and MOABC-QLSTM (Proposed) are 10.381%, 9.2992%, 8.2893%, 8.1021% and 3.8821%, respectively.

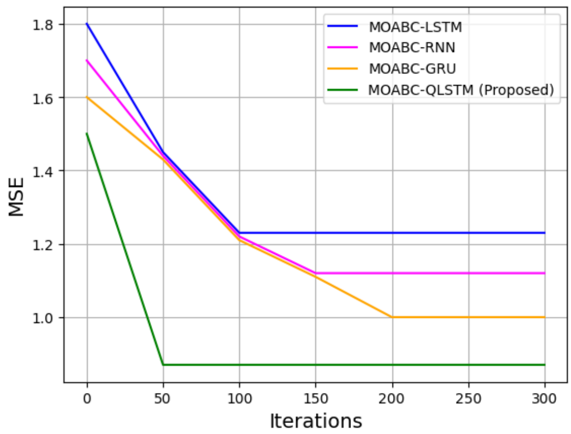


Fig. 5. Loss variation of each DL model under test dataset

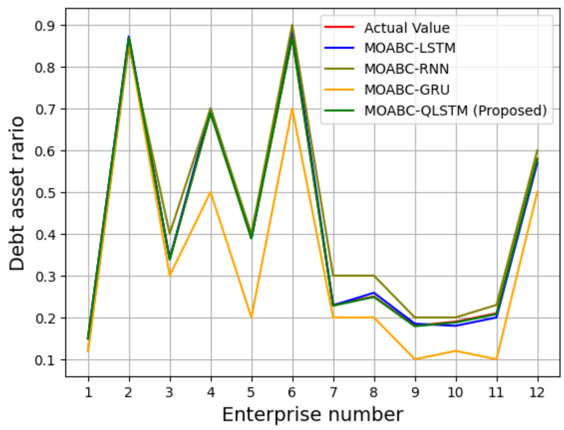


Fig. 6. Prediction of debt asset ratio of each approach

Table 4. Performance comparison under various approaches

Methods	R2 (%)	MSE	MAE	MAPE (%)
LSTM	89.22	0.0287	0.1372	10.381
MOABC-LSTM	96.28	0.0212	0.1278	9.2992
MOABC-RNN	95.39	0.0202	0.1183	8.2893
MOABC-GRU	91.24	0.0183	0.1082	8.1021
MOABC-QLSTM (Proposed)	99.78	0.0067	0.0562	3.8821

The model's efficacy is evaluated and contrasted with various established financial risk prediction systems, including FA-PSO-LSTM (Chen and Long, 2023), BPNN-BiLSTM (Zhao et al., 2024), DL-EWP (Dexiang et al., 2023), the Adaptive Whale Optimization Algorithm-based Deep Neural Network (AWOA-DNN) (Elhoseny et al., 2022), and MLP-ANN (Wu et al., 2022). This comparative analysis also demonstrates the effectiveness of the developed model in minimizing errors in predicting the financial risk of enterprises.

As a result, this study provides a more thorough demonstration of the MOABC-QLSTM fusion model's secured improved overall prediction performance than previous models in four areas: models, evaluation indicators, loss value variation, optimization procedures, and models.

4.4. Discussion

Although the study focuses on e-commerce firms, the MOABC-QLSTM framework itself is domain-agnostic because it relies on factor analysis and quantum-enhanced sequence modeling, both applicable to any multivariate financial time series. The MOABC optimization module automatically adapts hyperparameters, enabling scalability to larger datasets, additional indicators, and diverse industries. The model's architecture can therefore be extended to sectors such as manufacturing, banking, logistics, or fintech without methodological changes.

Table 5. Performance comparison with state-of-the-art approaches

Ref.,	Methods	MSE	MAPE (%)
Pouyanfar et al. (2018)	FA-PSO-LSTM	0.00738	4.887
Dexiang et al. (2023)	BPNN-BiLSTM	5.68	5.12
Elhoseny et al. (2022)	DL-EWP	0.4366	4.3822
Gu (2023)	AWOA-DNN	0.3627	4.1192
Liu et al. (2021)	MLP-ANN	0.1276	4.3812
Proposed	MOABC-QLSTM	0.0067	3.8821

After optimization, the Q-LSTM has computational demands similar to those of a standard LSTM, and the shallow VqC structure (two layers, four qubits) keeps quantum-inspired operations efficient on classical hardware. Additionally, factor analysis with a five-factor solution reduces input dimensionality, improving both speed and memory efficiency. Inference runs in near real time on modern CPUs/GPUs, though large-scale or high-frequency applications may require further model-lightening strategies.

The proposed approach uses a dataset comprising 12 e-commerce firms from 2012 to 2022, reflecting constraints on the availability of complete and consistent quarterly data. This small, sector-specific sample may limit the model's ability to generalize across industries with different financial structures. The absence of 2023–2024 data further limits evaluation under recent market conditions. Future work will incorporate larger, multi-industry, and multi-country datasets to strengthen robustness and external validity. Additional non-financial indicators will also be explored to improve generalizability

5. Conclusion

In the process of developing a digital economy, businesses encounter a variety of risks that are often unpredictable and beyond human control. Consequently, to grow and develop gradually in such an environment, it is crucial to develop a comprehensive plan to prevent a financial catastrophe before it occurs and to implement an early-detection and monitoring methodology for financial risk. During the model's construction, this paper draws on the popular DL prediction framework for time series forecasting to address the characteristics of business financial data. It subsequently identifies the shared factors among various financial and non-financial indicators through factor analysis to mitigate the risk of model overfitting. By comparing the risk prediction results, the proposed MOABC-QLSTM achieved a reduced MSE of 0.0067 and an MAPE of 3.8821%, with an increased R2 value of 99.78%. These results are superior to the comparison methods, such as MOABC-based LSTMs, RNNs, and GRUs. Even though the proposed fused DL model for financial risk prediction under the digital economy is superior, it has a limitation in terms of the smaller number of non-financial indicators used. In the future, the model will be enhanced by accounting for correlations among the non-financial indicators. Secondly, the proposed model is tested on other financial datasets to validate its generalization ability.

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Declaration of Artificial Intelligence (AI) Tools

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References

Cao, Y., Shao, Y., and Zhang, H. (2022). Study on early warning of E-commerce enterprise financial risk based on deep learning algorithm. *Electronic Commerce Research*, 22, 21-36.

Chen, X. and Cai, J. (2022). Digital transformation and financial risk prediction of listed companies. *Computational Intelligence and Neuroscience*, 2022, 7211033.

Chen, X. and Long, Z. (2023). E-commerce enterprises financial risk prediction based on FA-PSO-LSTM neural network deep learning model. *Sustainability*, 15(7), 5882.

Chicco, D., Warrens, M. J., and Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *Peer Journal Computer Science*, 7, e623.

Coello, C. and Lamont, G. (2004). Applications of multi-objective evolutionary algorithms. 1, *World Scientific*.

Dexiang, Y., Shengdong, M., Liu, Y., Jijian, G., and Chaolung, L. (2023). An improved deep-learning-based financial market forecasting model in the digital economy. *Mathematics*, 11(6), 1466.

Elhoseny, M., Metawa, N., Sztano, G. and El-Hasnony, I. (2022). Deep learning-based model for financial distress prediction. *Annals of Operations Research*. https://doi.org/10.1007/s10479-022-04766-5

Gao, J. (2022). Analysis of enterprise financial accounting information management from the perspective of big data. *International Journal of Scientific Research*, 11(3), 1272-1276.
Griol-Barres, I., Milla, S., Cebrián, A., Mansoori, Y., and Millet, J. (2021). Variational quantum circuits for machine learning. An application for the detection of weak signals. *Applied Sciences*, 11(14), 6427.
Gu, L. (2023). Optimized backpropagation neural network for risk prediction in corporate financial management. *Scientific Reports*, 13, 19330.
Gupta, V. and Li, Z. (2025). Advances in multi-objective swarm intelligence for financial forecasting and risk analytics. *Expert Systems with Applications*, 242, 122891.
He, Y., Xu, X., and Cai, Y. (2022). An evaluation of the effectiveness of three early-warning models on financial indexes. *Applied Economics Letters*, 29(20), 1880-1884.
Huang, W., Sun, X., and Zhao, L. (2025). Deep learning models for financial risk prediction in digital economies: A comprehensive review. *Information Sciences*, 660, 119987.
Huang, X., Zhang, Z., and Yuan, J. (2020). Predicting extreme financial risks on imbalanced dataset: A combined kernel FCM and kernel SMOTE based SVM classifier. *Computational Economics*, 56, 187-216.
Jang, Y., Jeong, I., and Cho, Y. (2020). Business failure prediction of construction contractors using a LSTM RNN with accounting, construction market, and macroeconomic variables. *Journal of Management in Engineering*, 36(4), 04019039.
Kamara, F., Chen, E., Liu, Q., and Zhen, P. (2020). A hybrid neural network for predicting Days on Market a measure of liquidity in real estate industry. *Knowledge-Based Systems*, 208, 106417.
Karaboga, D. (2005). An idea on honey bee swarm for numerical optimization. *Technical Report*, Erciyes University.
Karaboga, D. (2010). Artificial bee colony algorithm. *Scholarpedia*, 5(3), 6915.
Lai, W., Shi, J., and Chang, Y. (2023). Quantum-inspired fully complex-valued neutral network for sentiment analysis. *Axioms*, 12(4), 308.
Lei, Y. and Li, Y. (2022). Construction and simulation of the market risk early-warning model based on deep learning methods. *Scientific Programming*, 2022, 4733220.
Ling, T. and Cai, Y. (2022). Financial crisis prediction based on long-term and short-term memory neural network. *Wireless Communications and Mobile Computing*, 2022, 5728470.
Liu, M., Gao, R., and Fu, W. (2021). Analysis of internet financial risk control model based on machine learning algorithms. *Journal of Mathematics*, 2021, 8541929.
Liu, M., Gao, R., and Fu, W. (2021). Analysis of internet financial risk control model based on machine learning algorithms. *Journal of Mathematics*, 2021, 8541929.
Ma, Y. (2023). Application of deep learning in regional financial risk assessment and prediction. Highlights in Business, *Economics and Management*, 19, 660–665.
Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J.P., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N. and Antiga, L. (1912). Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems,* 32, 8024-8035.
Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M., Shyu, M., Chen, S., and Iyengar, S. (2018). A survey on deep learning: Algorithms, techniques, and applications. *ACM Computing Surveys*, 51(5), 1-36.
Qi, S., Jin, K., Li, B., and Qian, Y. (2020). The exploration of internet finance by using neural network. *Journal of Computational and Applied Mathematics*, 369, 112630.
Qiu, Y., Zhang, Q., and Lei, M. (2020). Forecasting the railway freight volume in China based on combined PSO-LSTM model. *Journal of Physics: Conference Series*, 1651(1), 012029.
Rahman, M., Lin, J., and Torres, P. (2024). Hybrid evolutionary–deep learning frameworks for corporate financial distress prediction. *Decision Support Systems*, 176, 114049.
Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics*, 9(1), 4-11.
Simjanović, D., Zdravković, N., and Vesić, N. (2022). On the factors of successful e-commerce platform design during and after COVID-19 pandemic using extended fuzzy AHP method. *Axioms*, 11(3), 105.
Singh, D., and Singh, B. (2020). Investigating the impact of data normalization on classification performance. *Applied Soft Computing*, 97, 105524.
Song, X., Jing, Y., and Qin, X. (2023). BP neural network-based early warning model for financial risk of internet financial companies. *Cogent Economics & Finance*, 11(1), 2210362.
Suddle, M. and Bashir, M. (2022). Metaheuristics based long short term memory optimization for sentiment analysis. *Applied Soft Computing*, 131, 109794.
Sun, Y. and Li, J. (2022). Deep learning for intelligent assessment of financial investment risk prediction. *Computational Intelligence and Neuroscience*, 2022, 3062566.
Trabelsi, C., Bilaniuk, O., Zhang, Y., Serdyuk, D., Subramanian, S., Santos, J., Mehri, S., Rostamzadeh, N., Bengio, Y., and Pal, C. (2017). *Deep Complex Networks*. arXiv preprint arXiv:1705.09792.
Wang, Z. (2022). A study on early warning of financial indicators of listed companies based on random forest. *Discrete Dynamics in Nature and Society*, 2022, 1314798.
Wu, D., Ma, X., and Olson, D. L. (2022). Financial distress prediction using integrated z-score and multilayer perceptron neural networks. *Decision Support Systems*, 159, 113814.
Zhao, X., Wang, W., Liu, G., and Vakharia, V. (2024). Optimizing financial risk models in digital transformation-deep learning for enterprise management decision systems. *Journal of Organizational and End User Computing*, 36(1).

Zhou, J., Li, W., Wang, J., Ding, S., and Xia, C. (2019). Default prediction in P2P lending from high-dimensional data based on machine learning. *Physica A: Statistical Mechanics and its Applications*, 534, 122370.
Zhou, Y., Chen, R., and Wang, T. (2024). Quantum-inspired neural sequence models for financial time-series prediction. *IEEE Transactions on Neural Networks and Learning Systems*, 35(7), 9541-9554.
Zhu, W., Zhang, T., Wu, Y., Li, S., and Li, Z. (2022). Research on optimization of an enterprise financial risk early warning method based on the DS-RF model. *International Review of Financial Analysis*, 81, 102140.

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