Hindawi
Discrete Dynamics in Nature and Society
Volume 2024, Article ID 9851850, 1 page
https://doi.org/10.1155/2024/9851850

Retraction

Retracted: A Dynamic Prediction Model of Financial Distress in the Financial Sharing Environment

Discrete Dynamics in Nature and Society

Received 23 January 2024; Accepted 23 January 2024; Published 24 January 2024

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Zhu, H. Zhu, and N. Lin, "A Dynamic Prediction Model of Financial Distress in the Financial Sharing Environment," *Discrete Dynamics in Nature and Society*, vol. 2023, Article ID 6259689, 11 pages, 2023.

Hindawi
Discrete Dynamics in Nature and Society
Volume 2023, Article ID 6259689, 11 pages
https://doi.org/10.1155/2023/6259689

Research Article

A Dynamic Prediction Model of Financial Distress in the Financial Sharing Environment

Jie Zhu[1], **Hong Zhu**[2], **and Nan Lin**[1]

[1]School of Finance and Accounting, Fuzhou University of International Studies and Trade, Fuzhou 350202, China
[2]School of Economics and Management, Fuzhou University of International Studies and Trade, Fuzhou 350202, China

Correspondence should be addressed to Nan Lin; linnan@fzfu.edu.cn

Received 3 December 2021; Revised 4 January 2022; Accepted 8 January 2022; Published 21 March 2023

Academic Editor: Ahmed Farouk

The dynamic prediction of financial distress can monitor the financial status of an enterprise in real time and provide evidence for financial analysts. However, currently, there are few studies concerning the dynamic prediction of financial distress in the financial sharing environment, so in order to fill this research gap, this study established a dynamic prediction model of financial distress in the financial sharing environment. Firstly, this study employed the analytic hierarchy process (AHP) and entropy weight theory to determine an index system for the dynamic evaluation of financial distress in the financial sharing environment and gave the weight assignment method of the evaluation indexes. Then, based on the probabilistic neural network (PNN), this study constructed a dynamic prediction model of financial distress and used experimental results to verify the effectiveness and feasibility of the constructed model.

1. Introduction

At the present time, the rapid development of information technologies such as cloud computing, big data, and mobile Internet has promoted the application of financial informatization [1–8], providing conditions for the realization of financial sharing services (FSS) [9–16]. The FSS mode not only realizes the information management and control of functional departments inside the companies but also greatly improves the efficiency and quality of financial information transmission, financial data processing, and analysis; however, at the same time, it also brings unprecedented challenges to the integrated financial information systems and reform of paperless audit environment [17–22].

In the emerging credit market, the demand for risk management increases day by day. Meanwhile, many new algorithms are emerging. As a result, the dynamic prediction of financial stress rises to prominence again. El Bannany et al. [23] studied the performance of various data mining models applied to the prediction of financial distress of companies in the Middle East and North Africa and optimized the multilayer perceptron model by adjusting hyperparameters such as network depth and width; at last, they used a real-time sample data set of companies in North Africa to evaluate the performance of the proposed prediction model. Sun et al. [24] divided the company's financial status into four types: sound status, false-sound status, moderate distressed, and severe distressed; then, the support vector machine (SVM) was combined with three kinds of decomposition and fusion methods of one-to-one, one-to-static, and error-correcting output codes to establish three multitype financial distress early-warning models. The prediction of corporate financial distress is very important to companies, investors, and regulators. However, most financial distress prediction models are established based on a single time dimension, and they generally ignore two key characteristics of the financial distress data: data set imbalance and data flow concept drift. Currently, financial stress prediction is being applied and studied in many financial fields as an important risk management tool. Shen et al. [25] proposed a new dynamic financial distress prediction method: the adaptive neighbor SMOTE recursive integrated approach, which allows multiple prediction results to be obtained from unbalanced data streams; through overall average AUC, it is found that the random forest classifier outperforms other commonly used classifiers in terms of data classification. Christopoulos et al. [26] assumed that liquidity and profitability constitute the key criteria for the status configuration of corporate financial distress status; then, with companies listed in the New York Stock Exchange as samples, they adopted a survival model based on dynamic logit to study the predictability of financial distress. In order to identify all the factors that have a significant impact on the company's financial status and rank them according to their relative importance, Mahtani et al. [27] adopted a multi-criteria decision-making method based on fuzzy AHP and further verified the robustness of the method through sensitivity analysis. Li et al. [28] extended the cross-sectional DEA model to the time-varying Malmquist DEA, and this decision support system can intelligently adjust the efficiency boundary over time and make robust predictions. The experimental results showed that, besides accurately predicting financial distress based on DEA efficiency measurement, the Malmquist DEA also provides insights into the company's competitive position.

After comprehensively reviewing the existing literature, it is found that although the research on financial distress prediction has achieved certain results, there are still problems that cannot be ignored, such as the dimensionality reduction of financial index data, the low prediction accuracy of integrated algorithms, and the negligence of the dynamic and unbalanced nature of sample data. In addition, currently, there are few studies concerning the dynamic prediction of financial distress in the financial sharing environment, so in order to fill in this research gap, this study establishes an index system for the dynamic prediction of financial stress in the financial sharing environment and further explores the integrated model for the dynamic forecast of financial stress. The main contents fall into two aspects: (1) Section 2 employs the analytic hierarchy process (AHP) and entropy weight theory to determine an index system for the dynamic evaluation of financial distress in the financial sharing environment and scientifically weighs the evaluation indexes. (2) Section 3 details the idea of building a dynamic prediction model for financial stress based on probabilistic neural network (PNN), clarifies the flow of input data processing and the construction process of PNN model and optimal combination prediction model. Finally, the model prediction was carried out in the light of timeliness, and the proposed model was proved feasible and effective through comparative experiments.

2. Determination of the Weights of Evaluation Indexes of the Prediction Model

After combing through the domestic and foreign literature on financial stress prediction in the financial sharing environment, it can be learned that the idea of sharing service has been well applied in some Chinese and foreign enterprises. However, this idea is still being explored for most enterprises. In addition, the relevant literature is fragmented. Most focus on theories and cases, while few talk about empirical research.

Based on the existing results, this study employs AHP and the entropy weight theory to construct a dynamic prediction model of financial distress in the financial sharing environment. In 1865, R. Clausius proposed the entropy weight theory, which illustrates the uniformity of spatial distribution of energy. Shannon applied this theory to information theory and put forward the information entropy weight. Referring to the analysis of the impact of specific financial sharing risks on the identification link of the dynamic significance of financial distress and the possible consequences, the analysis results were taken as the basis for the evaluation index selection of the proposed financial distress prediction model in this study.

Financial shared service (FSS) is the improvement direction of the current financial operation mode. FSS operation modes could be divided into four types of basic mode, market mode, advanced market mode, and independent business mode, which respectively aim at the functional departments inside the company, the responsible entities that operate independently, and the profit organizations. Figure 1 gives a schematic diagram of the FSS operation modes. As shown in the figure, according to the development trend of FSS, the four operation modes develop progressively over time. Figure 2 shows the process framework of FSS. Only by fully integrating the existing financial systems and realizing the standard FSS process, specific applications of the FSS technology can be guaranteed. According to Figure 2, the process of FSS contains 11 first-level procedures including tax accounting, FSS data maintenance, financial report analysis, and general ledger accounting of the financial system, etc., and under this framework, there are more-detailed second-level procedures and specific businesses. The advancement progress of FSS mode is greatly affected by the framework of the sharing process.

Following principles of pertinence, comparability, and operability, this study analyzes actual FSS cases and selects 6 major financial distress types to construct the first-level evaluation indexes for judging whether there is financial distress in the financial system in the financial sharing environment, and then, the 6 first-level evaluation indexes were further divided into 28 second-level evaluation indexes, representing subtypes of the financial distress; together these indexes constituted a relatively complete evaluation index system of financial distress in the financial sharing environment. Each type of financial distress involves different financial risk items, and all these evaluation indexes are closely related to the financial distress and its dynamic changes during the FSS implementation process.

The evaluation target of the evaluation index system is the dynamic evaluation result of financial distress based on the application of the FSS system (FD). The 6 first-level evaluation indexes include strategy planning FD_1, organization management FD_2, financial analysts FD_3, financial risk control process FD_4, financial system construction FD_5, and compliance operation management FD_6. Strategy planning FD_1 contains 6 second-level indexes: strategy formulation conflict FD_{11}, insufficient preparation for system implementation FD_{12}, unreasonable center location

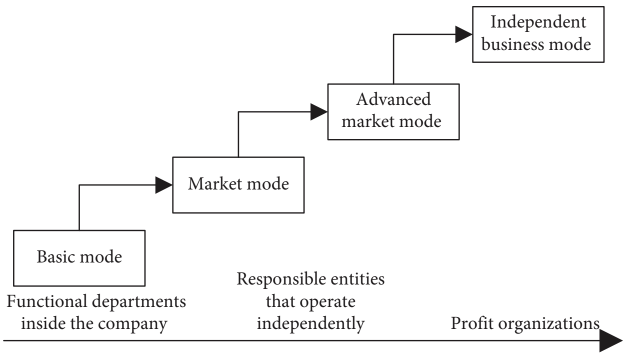

Figure 1: Operation modes of FSS.

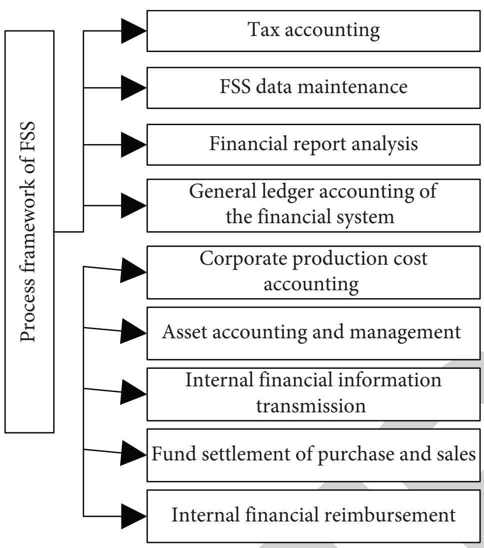

Figure 2: Overall process framework of FSS.

FD_{13}, unreasonable financial business scope definition FD_{14}, management's emphasis on risks FD_{15}, excessive initial investment and operation management costs FD_{16}. Organization management FD_2 contains 4 second-level indexes: internal conflicts of financial organization FD_{21}, unintegrated financial and business departments FD_{22}, unreasonable organization structure FD_{23}, and unreasonable system formulation FD_{24}. Financial analysts FD_3 contains 3 second-level indexes: difficult internal communication of financial analysts FD_{31}, financial analysts' insensitivity to data FD_{32}, and nonstandard operation of financial analysts FD_{33}. Financial risk control process FD_4 contains 5 second-level indexes: non-standard instruction for initial process operations FD_{41}, unreasonably designed standard process FD_{42}, difficult integration of financial business processes FD_{43}, lack of balance control FD_{44}, and poor adaptability of new process FD_{45}. Financial system construction FD_5 contains 5 second-level indexes: system integration inability FD_{51}, unreasonable system development and design FD_{52}, weak system support FD_{53}, insufficient system stability FD_{54}, and insufficient system electronic data security FD_{55}. Compliance operation management FD_6 contains 5 second-level indexes: noncompliant organizational form of the system FD_{61}, noncompliant system operation mode FD_{62}, noncompliant system authority setting FD_{63}, corporate and financial operation risks FD_{64}, and incomplete internal audit system FD_{65}.

Figure 3 gives a scree plot of the evaluation indexes. According to the figure, when the abscissa is greater than 6, the eigenvalue of the evaluation indexes is less than 2, and the curve tends to become flattered, indicating that an inflection point appeared after the 6-th evaluation index, and this has also verified that it is reasonable to extract 6 types of financial distress.

If a financial system has m different dynamic distress statuses, which are represented by $R_1, R_2, R_3, \ldots, R_m$, and the probability values corresponding to each status are represented by $QA_1, QA_2, QA_3, \ldots, QA_m$, then the dynamic information volume of the uncertain financial distress of the system can be described by the following formula:

$$D - \sum_{i=1}^{m} QA_i \ln QA_i, \text{ satisfies } 0 \le QA_i \le 1 \quad (i = 1, 2, 3, \ldots, m), \qquad \sum_{i=1}^{m} QA_i = 1. \tag{1}$$

The entropy weight method was used in the dynamic prediction model of financial distress in the financial sharing environment and taken as the method for determining the weight values of the model indexes. If the dynamic evaluation of financial distress needs to measure m types of factors and ω_{ij} represents the evaluation index of factor FD, then it satisfies the following formula:

$$\sum_{j=1}^{n} \omega_{ij} = 1 \quad (i = 1, \ldots, m;\ j = 1, \ldots, n). \tag{2}$$

The relative importance of FD_i can be measured by entropy value:

$$D_i = -\sum_{j=1}^{n} \omega_{ij} \ln \omega_{ij}. \tag{3}$$

The relative importance of FD_i was normalized, and the entropy value of the relative importance of FD_i was calculated by the following formula:

$$s_i = -\frac{1}{\ln n} \sum_{j=1}^{n} \omega_{ij} \ln \omega_{ij}. \tag{4}$$

The weight of FD_i can be determined based on $1 - s_i$ using the following formula:

$$\psi_i = \frac{1}{m - P} (1 - s_i) \left(0 \le \psi_i \le 1, P = \sum_{i=1}^{m} s_i, \sum_{i=1}^{m} \psi_i = 1 \right). \tag{5}$$

3. Research Methods of the Prediction Model

3.1. Model Analysis Steps. The specific analysis steps of the proposed dynamic prediction model of financial distress constructed based on AHP and entropy weight theory are described in detail as follows:

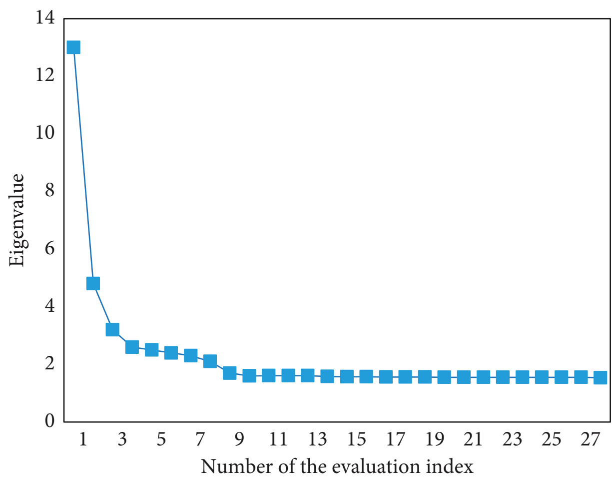

Figure 3: The screen plot of evaluation indexes.

Step 1. Modeling foundation Basic works of constructing the proposed model are as follows: (1) correctly selecting dynamic evaluation indexes of financial distress; (2) reasonably setting the scope of the conformance weight of the prediction model; (3) scientifically defining the level of significance of financial distress in the financial sharing environment.

Step 2. Assign values to the conformance weight β_{ijl} of the second-level evaluation indexes in the third layer of the prediction model.

Step 3: Suppose that the number of inducing factors corresponding to the i-th type of financial distress is represented by q, and the number of control measures corresponding to the j-th inducing factor of the i-th type of financial distress is represented by e, then, based on the following formula, the entropy value α_{ij} and weight ψ_{ij} of the second-level indexes, namely, the second layer of the model can be measured as follows:

$$\alpha_{ij} = -\frac{1}{\ln e}\sum_{l=1}^{e}\beta_{ijl}\ln \beta_{ijl};\ \phi_{ij} = \frac{\left(1-\alpha_{ij}\right)}{\left(q-\sum_{j=1}^{q}\alpha_{ij}\right)}. \tag{6}$$

In order to make the data of the evaluation indexes meet the calculation requirements of the entropy weight method, it is necessary to normalize β_{ijl} before the calculation of α_{ij}, and then use the formula to calculate weight value ψ_{ij} corresponding to α_{ij}.

Step 4: Based on the following formula, the entropy value γ_i and the corresponding weight ψ_i of the evaluation indexes in the first layer of the model could be calculated:

$$\begin{aligned}\gamma_i &= -\frac{1}{\ln q}\sum_{j=1}^{q}\phi_{ij}\ln \phi_{ij};\\ \phi_i &= \frac{\left(1-\gamma_i\right)}{\left(q-\sum_{j=1}^{q}\gamma_i\right)}.\end{aligned} \tag{7}$$

Step 5: Suppose the number of evaluation indexes under the overall significance level of the target layer (namely, the financial distress in the financial sharing environment) is represented by g, then, based on the following formula, the entropy value d and weight value ψ of the overall significance of the target layer (the financial distress in the financial sharing environment) could be calculated as follows:

$$\begin{aligned}d &= -\frac{1}{\ln g}\sum_{j=1}^{g}\phi_i \ln \phi_i;\\ \phi &= 1-d.\end{aligned} \tag{8}$$

The PNN, proposed by Dr. Specht in 1988, is a multilayer hierarchical neural network. This study adopts the model to dynamically evaluate and predict the financial stress in the financial sharing environment. The input data of the network were a grayscale image composed of the data of indexes from year $\tau-1$ to year $\tau-w$, and the indexes were divided into two types: quantitative indexes and qualitative indexes. In this study, the data of these two types of indexes were processed respectively, and the specific steps are introduced as follows:

3.2. Input Data Processing. After normalization, the value range of all elements in the matrix formed by the evaluation index data of the corporate financial system to be evaluated satisfied [0, 1]. The matrix was converted into a grayscale image that uses pixel value to represent the shade of the color; the pixel value range was [0, 255], and 0 and 255, respectively, represent absolute black and absolute white. The value range of the index data was transformed from [0, 1] to [0, 255], and the obtained integer value was represented by $U\left(A^{\tau-}w_{ij}\right)$:

$$U\left(A_{ij}^{\tau-w}\right) = \langle A_{ij}^{\tau-w} * 255\rangle. \tag{9}$$

Among them, <x> means to take the integer part of x. Based on the idea of energy minimization, the excepted grayscale image could be generated, and the specific steps are as follows:

Step 1: Initialize settings.

The M evaluation indexes of the i-th corporate financial system to be evaluated in the τ-th year were arranged in a $M^{1/2}\times M^{1/2}$ matrix from top to bottom and from left to right, and the set of the corresponding serial numbers of the evaluation indexes was represented by $O=\{1,2,\ldots,M\}$. Then, the initial grayscale image was generated based on the matrix and represented by $\mathrm{GP}_{i,0}^{\tau}$. Suppose, $\mathrm{NS}^{\tau-w}$ represents the energy of a company in the $\tau-w$-th year, $q^{\tau-w}(V(j_1), V(j_2))$ represents the correlation coefficient between $V(j_1)$ and $V(j_2)$ in the $\tau-w$-th year, and $V(j)$ represents the value corresponding to the j-th index, then the following formula gives the expression of $\mathrm{NS}^{\tau-}w$, the energy of the grayscale image:

$$NS^{\tau-w} = \sum_{(j_1,j_2)} \left|q^{\tau-w}[V(j_1),V(j_2)]\right|\xi^{\tau-w}(j_1,j_2). \tag{10}$$

Suppose, $\xi^{\tau-}w(j_1, j_2)$ represents the distance between the j_1-th index and the j_2-th index in the $\tau-w$-th year, $a^{\tau-}w\ (j_1)$ and $b^{\tau-}w\ (j_1)$ respectively represent the abscissa and ordinate of the pixel corresponding to the j_1-th index in the $\tau-w$-th year, then there is

$$\xi^{\tau-w}(j_1,j_2) = \left(a^{\tau-w}(j_1) - a^{\tau-w}(j_2)\right)^2 + \left(b^{\tau-w}(j_1) - b^{\tau-w}(j_2)\right)^2. \tag{11}$$

The data of the evaluation indexes of the i-th company in the $\tau-w$-th year were converted to generate an initial grayscale image $\mathrm{GP}_{i,0}^{\tau-w}$ with an initial energy $\mathrm{NS}_0^{\tau-w}$.

Step 2. Randomly select two pixels in $\mathrm{GP}_{i,0}^{\tau-w}$ and exchange their positions. If the energy value of the grayscale image can be reduced, then the positions are exchanged; otherwise, they are not exchanged.

Step 3: Repeat the previous step. When the number of repetitions reaches 3 times the number of evaluation indexes and there is still no pixel position swap, terminate the repetition operation and output the exchanged image $\mathrm{GP}_i^{\tau-w}$ and the corresponding energy $\mathrm{NS}^{\tau-}w$.

3.3. Modeling of the PNN. After grayscale image $\mathrm{TW}^{\tau-}w_i$ ($w=1, 2, 3, 4, 5$; $i=1, 2, \ldots, N$) of the $\tau-w$-th year of the i-th corporate financial system to be evaluated was input into the PNN, the evaluation prediction result ($\mathrm{DR}_i^{\tau-w}$, $1-\mathrm{DR}_i^{\tau-w}$) could be obtained. Wherein, $\mathrm{DR}_i^{\tau-w}$ represents the probability that the financial system of the i-th company to be evaluated is evaluated as in financial distress in the time window of the $\tau-w$-th year; $1-\mathrm{DR}_i^{\tau-w}$ represents the probability that the financial system of the i-th company to be evaluated is evaluated as not in financial distress in the time window of the $\tau-w$-th year.

Taking the grayscale images of the $\tau-w$-th year corresponding to N companies to be evaluated as the input variables of the PNN, then, based on the activation function, the following equation could be constructed:

$$CZ_{\tau-w}^{\tau} = G\left(A_{\tau-w}, \omega_{\tau-w}\right). \tag{12}$$

The output of formula (12) is $\mathrm{CZ}_{\tau-w}^{\tau}(w=1, 2, 3, 4, 5)$, namely, the financial status of the financial system of the company to be evaluated of the τ-th year in the time window of the $\tau-w$-th year. Suppose, TP_i^{τ} represents the real status of the financial system of the i-th company to be evaluated in the τ-th year, then, in order to describe the output variable more clearly, in this study, the data of the financial system of the i-th company to be evaluated in the τ-w-th year are written in the form of W arrays of $(\mathrm{TW}_i^{\tau-1}, \mathrm{TP}_i^{\tau})$, $(\mathrm{TW}_i^{\tau-2}, \mathrm{TP}_i^{\tau})$, $(\mathrm{TW}_i^{\tau-3}, \mathrm{TP}_i^{\tau})$, $(\mathrm{TW}_i^{\tau-4}, \mathrm{TP}_i^{\tau})$, and $(\mathrm{TW}_i^{\tau-5}, \mathrm{TP}_i^{\tau})$.

PNN is a neural network model containing multiple layers of input layer, pattern layer, summation layer, and output layer. Figure 4 shows the structure of the constructed PNN model. Since the evaluation of financial distress in the financial sharing environment is a kind of two-category problem, the output of the model is the final category of the input grayscale image.

Bayesian discriminant analysis and probability density function together constitute the basic theories of PNN. Assuming in a financial distress classification problem in the financial sharing environment, $a^{(n)} = [a_1, a_2, \ldots, a_m]$ represents the $n\times m$ dimension input grayscale image, if XR_z represents the prior probability that the input grayscale image belongs to the z-th category, BD_z represents the penalty cost for wrong classification, $\mathrm{SD}_z(a)$ represents the probability density function, then the following formula gives the expression of Bayesian discriminant analysis:

$$XR_i BD_i SD_i(a) > XR_j BD_j SD_j(a) \quad \forall j \neq i. \tag{13}$$

Formula (13) describes that the grayscale image input this time belongs to the i-th category. For the three variables of prior probability, penalty cost, and probability density function, it is quite difficult to find an ideal probability density function $\mathrm{SD}(a)$. In order to solve this problem, this study chose to introduce the Parzen window theory to estimate the probability density function using a supervised training set and use a Gaussian function to express it. Suppose, A represents the input grayscale image, A_j represents the central grayscale image coming from the entire training set, and ε represents the smoothing parameter, then there is

$$SD_j(A) = \exp\left[= \frac{\left(A - A_j\right)^2}{2\varepsilon^2}\right]. \tag{14}$$

Based on the above formula, the probability density function of the j-th neuron node of the pattern layer could be obtained, which is represented by $\mathrm{SD}_j(A)$ ($\forall j = 1, 2, \ldots, M$). The HU that describes the category attribute from the pattern layer to the summation layer is an $M\times 2$ dimensional vector, which can be denoted as $\mathrm{HU}_{M\times 2} = [\delta_{ij}](\forall i = 1, 2, \ldots, M; \forall j = 1, 2)$. Suppose, $SP = [\mathrm{SD}_1(A), \mathrm{SP}_2(A), \ldots, \mathrm{SP}_j(A), \ldots, \mathrm{SD}_M(A)]$ represents the vector constituted by the probability density functions of all neuron nodes in the pattern layer, then the following formula gives the calculation formula of the output result of the training grayscale image samples in the network summation layer:

$$\begin{aligned} HA &= SP \cdot HU \\ &= \left[SD_1(A), SD_2(A), \ldots, SD_j(A), \ldots SD_M(A)\right] \\ &\quad \cdot \left[\delta_{ij}\right]_{M\times 2}. \end{aligned} \tag{15}$$

Normalize HA to get

$$\overline{HA} = \frac{HA}{\left(HA \cdot DW^T\right)}. \tag{16}$$

Let HA represent the real evaluation result of a certain sample, and if the training grayscale image sample belongs to the i-th category, then only the i-th element is equal to 1. The

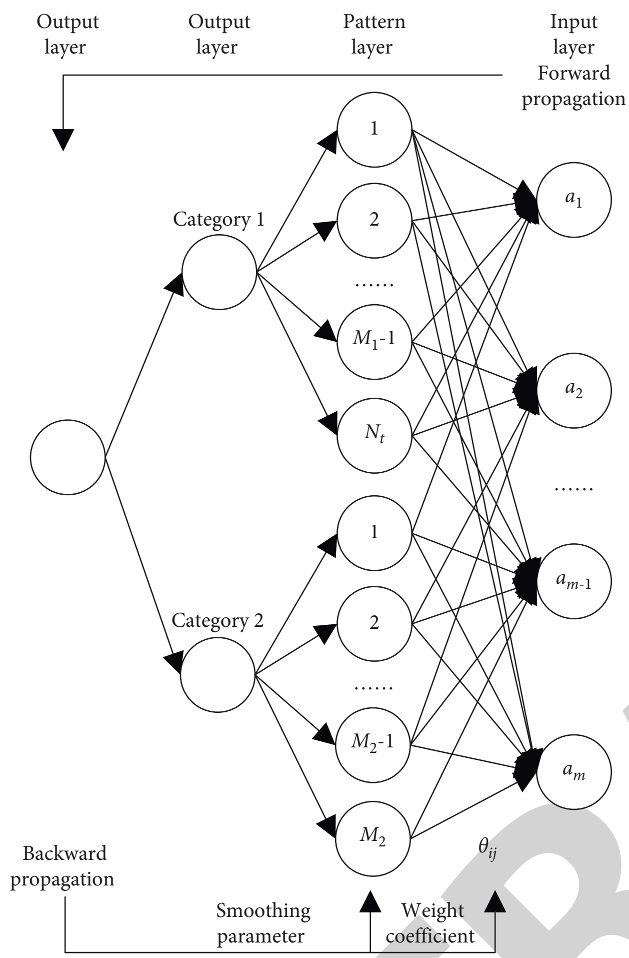

Figure 4: Structure of the constructed PNN.

calculation formula of the error function of the sample evaluation result is given as follows:

$$WC = 1 - \overline{HA} \cdot \left(HA'\right)^T. \tag{17}$$

The above formula is the error function designed for the constructed PNN, and the value range of the error value WC is [0, 1]. The greater the value of the i-th element in the vector output by the network, the closer the evaluation result is to the real evaluation result, and the closer the WC is to 0. Especially when the evaluation result is equal to the real evaluation result, WC is equal to 0. By substituting formulas (15) and (16) into formula (17), the specific error function of the constructed PNN could be obtained:

$$WC = 1 - \frac{SP \cdot HU \cdot (HA')^T}{SP \cdot HU \cdot DW^T}. \tag{18}$$

Among the parameters in the constructed PNN, θ_{ij} represents the weight coefficient between the i-th neuron node in the input layer and the j-th neuron node in the pattern layer, then there is

$$\theta_{ij} = \frac{a_i}{\sum_{\delta=1}^{m} a_\delta^{2\,1/2}}. \tag{19}$$

Suppose, a_i represents the index value of the i-th column of the input grayscale image, then A and A_j in formula (14) can be calculated by formulas (20) and (21), respectively:

$$A = \sum_{i=1}^{m} a_i \cdot \theta_{ij}, \tag{20}$$

$$A_j = \sum_{i=1}^{m} a_i' \cdot \theta_{ij}. \tag{21}$$

Suppose, a_i' represents the j-th neuron node in the pattern layer, namely, the index value of the i-th column of the j-th sample data in the grayscale image training set. The two formulas were substituted into SP = [$SD_1(A)$, $SP_2(A)$, . . ., $SP_j(A)$, . . ., $SD_M(A)$], and then the SP was brought into the error function and its derivative was taken. Assuming η represents the learning rate, by letting the derivative of the error function be equal to 0, the update of the weight coefficient could be completed:

$$\begin{aligned}\Delta\theta_{ij} &= -\eta \cdot \frac{\partial W\ C}{\partial\theta_{ij}} \\ &= -\eta \cdot \frac{\partial S\ P/\partial\theta_{ij} \cdot HU \cdot (HA')^T \cdot SP \cdot HU \cdot DW^T - SP \cdot HU \cdot (HA'')^T \cdot \partial S\ P/\partial\theta_{ij} \cdot HU \cdot HA^T}{\left(SP \cdot HU \cdot DW^T\right)^2}.\end{aligned} \tag{22}$$

Specific to the j-th probability density function in SP, based on formulas (14), (20), and (21), the update formula of the weight coefficient could be derived:

$$\frac{\partial S\ D_j}{\partial\theta_{ij}} = \frac{\theta_{ij} \cdot (a_i - a_i')^2}{\varepsilon_j^2} \cdot \exp\left[-\frac{\sum_{z=1}^{m} \theta_{zj}^2 \cdot (a_z - a_z')^2}{2\varepsilon_j^2}\right]. \tag{23}$$

Further, the expression of the set vector could be obtained as follows:

$$\frac{\partial S\ P}{\partial\theta_{ij}} = \left(\frac{\partial S\ D_1(A)}{\partial\theta_{ij}}, \frac{\partial S\ D_2(A)}{\partial\theta_{ij}}, \ldots, \frac{\partial S\ D_j(A)}{\partial\theta_{ij}}, \ldots, \frac{\partial S\ D_m(A)}{\partial\theta_{ij}}\right). \tag{24}$$

Finally, by combining formulas (23) and (24) with formula (22), the final weight coefficient update formula can be obtained.

Referring to the update process of the weight coefficient, the smoothing parameter of the network was updated, and the update formula is given by the following equation:

$$\Delta\varepsilon_j = -\eta\cdot\frac{\partial W\ C}{\partial\varepsilon_j} = -\eta\cdot\frac{\partial S\ P/\partial\varepsilon_j\cdot HU\cdot(HA\prime)^T\cdot SP\cdot HU\cdot HA^T - SP\cdot HU\cdot(HA\prime)^T\cdot\partial S\ P/\partial\varepsilon_j\cdot HU\cdot HA^T}{\left(SP\cdot HU\cdot HA^T\right)^2}. \tag{25}$$

Specifically, the smoothing parameter update formula of the j-th neuron node in the pattern layer is given as follows:

$$\frac{\partial S\ D_j}{\partial\varepsilon_j} = \frac{\sum_{z=1}^{m}\theta_{zj}^2\cdot\left(a_z - a_z'\right)^2}{\varepsilon_j^3}\cdot\ \exp\left[-\frac{\sum_{z=1}^{m}\theta_{zj}^2\cdot\left(a_z - a_z'\right)^2}{2\varepsilon_j^2}\right]. \tag{26}$$

Further, the calculation formula of the set vector could be given as follows:

$$\frac{\partial S\ P}{\partial\varepsilon_j} = \left(\frac{\partial S\ D_1(A)}{\partial\varepsilon_j}, \frac{\partial S\ D_2(A)}{\partial\varepsilon_j}, \ldots, \frac{\partial S\ D_j(A)}{\partial\varepsilon_j}, \ldots, \frac{\partial S\ D_m(A)}{\partial\varepsilon_j}\right). \tag{27}$$

Similarly, at last, by combining formula (26) with formulas (27) and (25), the final smoothing parameter update formula could be obtained.

3.4. Construction of the Optimal Combination Prediction Model. In a financial sharing environment, the dynamic evaluation of financial distress needs to consider the information content volume and timeliness of the evaluation index data. The information content volume of the evaluation index data of financial distress decreases with the passage of time, that is, the shorter the time from the occurrence of the financial distress, the greater the information content volume of the evaluation index data, and the higher the accuracy of the evaluation result. Conversely, the longer the time from the occurrence of the financial distress, the smaller the information content volume of the evaluation index data, and the lower the accuracy of the evaluation results. In order to find the optimal ratio of different time windows, this study comprehensively considered the impact of different time periods on the financial distress evaluation of the financial system of each company to be evaluated.

Suppose, BR represents the fold number of the cross-validation; $\mathrm{DR}^{\tau-}w_i, \nu$ represents the probability that the ν–th fold ($rv = 1, 2, \ldots,$ BR) of the financial system of the i-th company to be evaluated is evaluated as in financial distress in the τ-th year predicted in the time window of the $\tau - w$-th year; $1 - DR^{\tau}\ w_i, \nu$ represents the probability that the ν-th fold of the financial system of the i-th company to be evaluated is evaluated as not in financial distress in the τ-th year predicted in the time window of the $\tau - w$-th year; TP w_i, ν ($i = 1, 2, \ldots, N$) represents the real probability that the ν-th fold of the financial system of the i-th company to be evaluated is evaluated as in financial distress; $1 - \mathrm{TP}\ w_i, \nu$ represents the real probability that the ν-th fold of the financial system of the i-th company to be evaluated is evaluated as not in financial distress; $\Psi_{\tau\,-}w$ represents the parameter that describes the heterogeneity information of different years to be estimated, and then, based on the grayscale image verification sample set and the optimization model, the time window could be weighted as follows:

$$\begin{aligned}
&\min_{\Psi_{\tau-1},\Psi_{\tau-2},\Psi_{\tau-3},\Psi_{\tau-4},\Psi_{\tau-5}} \frac{1}{BR}\sum_{\nu=1}^{BR}\left(\sum_{i=1}^{N}\left(\left(\sum_{w=1}^{5}\Psi_{\tau-\sigma}\theta_{i,\nu}^{\tau-w} - TP_{i,\nu}^{\tau}\right)^2\right.\right.\\
&\left.\left.+\left(\sum_{w=1}^{5}\Psi_{\tau-w}\left(1-\theta_{i,\nu}^{\tau-w}\right) - \left(1 - TP_{i,\nu}^{\tau-w}\right) - \left(1 - TP_{i,\nu}^{\tau}\right)\right)^2\right)\right)\\
&\Leftrightarrow \min_{\Psi_{\tau-1},\Psi_{\tau-2},\Psi_{\tau-3},\Psi_{\tau-4},\Psi_{\tau-5}} \frac{1}{BR}\sum_{\nu=1}^{BR}\sum_{i=1}^{N}\left(\sum_{w=1}^{5}\Psi_{\tau-w}\theta_{i,\nu}^{\tau-w} - TP_{i,\nu}^{\tau}\right)^2,
\end{aligned} \tag{28}$$

$$s.t. 0 < \Psi_{\tau-w} < 1; \quad w = 1, 2, 3, 4, 5, \tag{29}$$

$$\Psi_{\tau-5} < \Psi_{\tau-4} < \Psi_{\tau-3} < \Psi_{\tau-2} < \Psi_{\tau-1}, \tag{30}$$

$$\sum_{w=1}^{5}\Psi_{\tau-w} = 1; \quad w = 1, 2, 3, 4, 5. \tag{31}$$

4. Experimental Results and Analysis

Judging whether there are correlations between the evaluation indexes and different types of financial distress and determining the degree of relevance are the key points of the research on the dynamic prediction of financial distress in the financial sharing environment. In this study, the Pearson correlation analysis in SPSS 22.0 was selected to search for

Table 1: Correlation analysis of first-level evaluation indexes and different types of financial distress—Part 1.

	Increased cost		Low financial service quality		Low accuracy of financial information security	
	Pearson correlation	Significance	Pearson correlation	Significance	Pearson correlation	Significance
FD_1	0.658^{**}	0.001	0.769^{**}	0.000	0.769^{**}	0.000
FD_2	0.615^{**}	0.002	0.678^{*}	0.001	0.538^{**}	0.000
FD_3	0.531^{**}	0.001	0.485^{**}	0.000	0.438^{*}	0.023
FD_4	0.325^{*}	0.021	0.536^{*}	0.000	0.623^{**}	0.000
FD_5	0.224^{**}	0.235	0.325^{**}	0.027	0.368^{*}	0.045
FD_6	0.268^{**}	0.276	0.427^{*}	0.003	0.769^{**}	0.000

Note. **Significant correlation at the 0.1 significance level; *significant correlation at the 0.05 significance level.

Table 2: Correlation analysis of first-level evaluation indexes and different types of financial distress–Part 2.

	Uncoordinated financial business works		Talent loss	
	Pearson correlation	Significance	Pearson correlation	Significance
FD_1	0.786^{**}	0.001	0.576^{**}	0.002
FD_2	0.538^{*}	0.003	0.486^{*}	0.001
FD_3	0.425^{**}	0.001	0.528^{**}	0.003
FD_4	0.613^{**}	0.002	0.436^{**}	0.000
FD_5	0.345^{*}	0.003	0.258^{*}	0.002
FD_6	0.382^{**}	0.001	0.438^{**}	0.003

Note. **Significant correlation at the 0.1 significance level; *significant correlation at the 0.05 significance level.

the direction and degree of the linear relationship between variables and complete the correlation analysis according to the importance degree of the evaluation indexes. In order to show the correlations between various evaluation indexes and different types of financial distress more intuitively, Tables 1 and 2 give the results of the correlation analysis of the first-level evaluation indexes and the different types of financial distress. The main content of the tables is the results of the Pearson correlation coefficients and significance levels of the 6 evaluation indexes and each type of financial distress (including increased cost, low financial service quality, low accuracy of financial information security, uncoordinated financial business works, and talent loss). According to the data in the tables, we can know that all of them had passed the 5% significance level tests, and it can be concluded that all first-level evaluation indexes have significant correlations with the different types of financial distress.

In order to find the optimal weight coefficient of multiple windows, based on PNN, this study constructed an optimal combination prediction model, which had effectively improved the accuracy of the prediction model and the evaluation values, and its performance was compared with the traditional neural network, decision tree, SVM, and logistic regression in terms of single time window, as listed in Table 3. According to the table, the proposed model outperformed the other methods in terms of prediction accuracy, AUC value, and KS value. At the same time, it is known that a time window with high prediction accuracy may obtain less weight in the optimal combination optimization model, that is, the time window is not completely consistent with the significance of the financial distress. This is the result after comprehensively considering the information of different time windows, and it is also the requirement for obtaining the overall optimal prediction effect.

According to the combination ratios of 4:1 and 3:1, the unbalanced sample data of financial distress evaluation indexes were constructed, and the corresponding prediction model was built. Figure 5 shows the model prediction results before and after considering timeliness. Too small a comparison window can easily lead to insufficient model training, while too large a comparison window can lead to data confusion under different concepts. From the perspective of the width of different windows, when the width is 5, the probability of obtaining the optimal financial distress prediction result is higher, and this makes the model prediction results of different combination ratios exhibit a trend of higher in the middle and lower in both ends.

In this study, the performance of the model before and after adding the sliding time window was compared and analyzed; Table 4 gives the model prediction results before and after considering the timeliness. First, in terms of the specificity indicator, the prediction results of the model considering timeliness had all reached an accuracy of more than 90%, while for the model without the sliding time window, the accuracy was only 82.74%, which was slightly lower than the former. Second, in terms of the sensitivity indicator, the optimal accuracy of model considering timeliness was 94.86%, and this value of model without the sliding time window was 87.64%, which was still slightly lower than the former. It can be considered that the model considering timeliness and adding the sliding time window can effectively solve the problem of dynamic evaluation of financial distress in the financial sharing environment, while the original model before considering timeliness only had divided the data samples based on subjective decisions; a

Table 3: Evaluation and prediction performance of different evaluation models.

Year	2018			2019			2020		
Evaluation criterion	Acc	AUC	KS	Acc	AUC	KS	Acc	AUC	KS
Traditional neural network	68.74%	0.7582	0.3684	68.47%	0.7286	0.3712	72.82%	0.7485	0.4385
Decision tree	70.58%	0.4253	0.4275	76.24%	0.5425	0.5347	71.38%	0.4752	0.4527
SVM	75.81%	0.5273	0.5724	79.75%	0.6273	0.5372	72.47%	0.5347	0.4627
Logistic regression	67.34%	0.4725	0.3752	69.35%	0.4572	0.3827	64.28%	0.4275	0.2684
Proposed model	82.14%	0.4014	0.3544	86.52%	0.3945	0.3477	82.97%	0.4149	0.2787

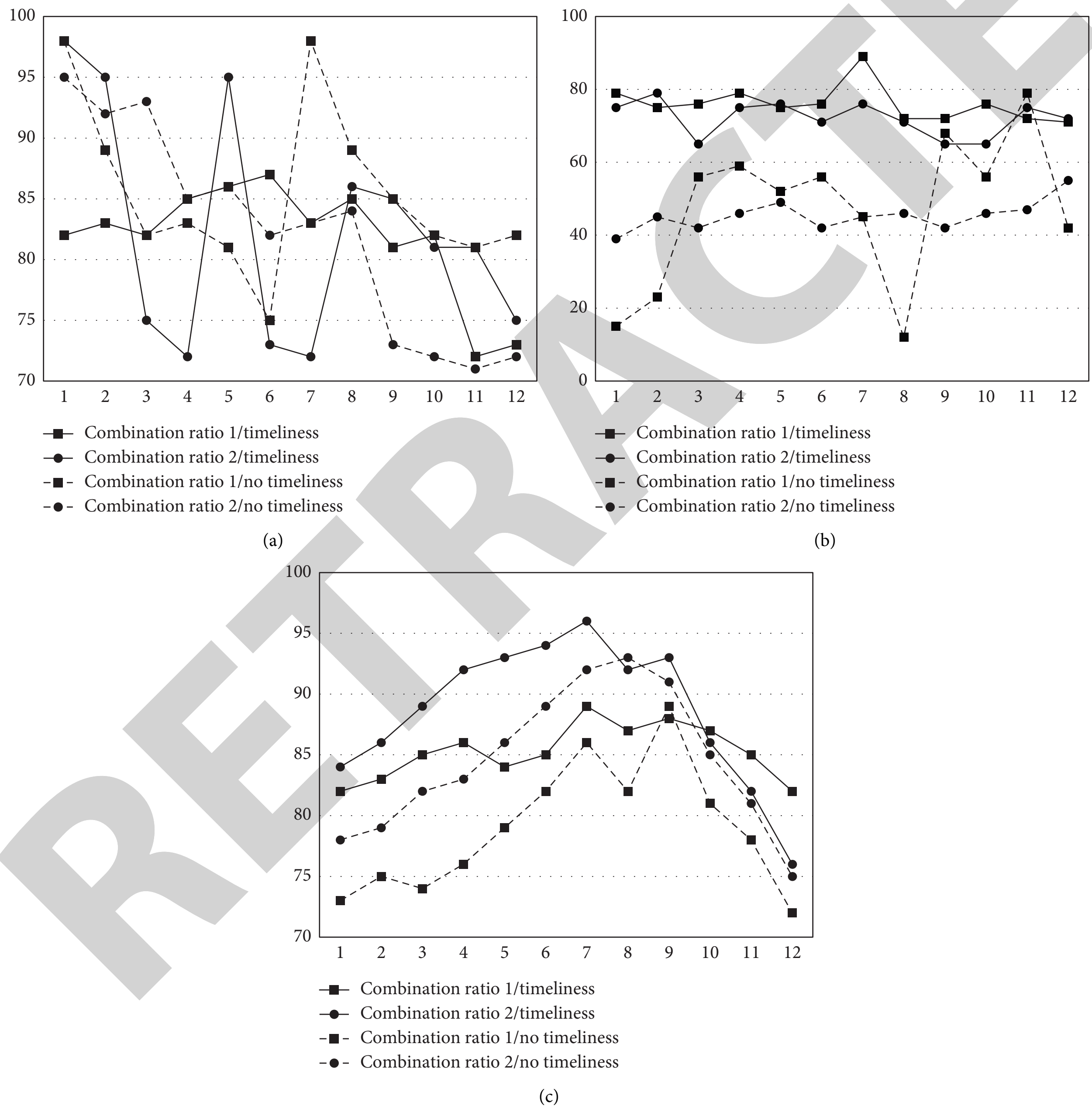

Figure 5: Comparison of model prediction results under different combination ratios.

Table 4: Model prediction results before and after considering timeliness.

Model		Before considering timeliness			After considering timeliness		
Performance indicator		Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
Window width (year)	1	82.45	85	82	95.32	87	92
	2	88.62	87	86	89.03	92	91
	3	86.34	95	86	86.84	93	97
	4	93	81	83	82.01	95	94
	5	86.57	82	85	81.34	95	92
	6	93	88	84	83.04	87	93
	7	90.52	85	83	77.58	95	98
	8	89.56	82	85	75.02	95	96
Mean		87.34	87.64	82.74	83.24	94.86	95.03

training set included sample data of different concepts and different attributes, which had resulted in a decline in the prediction performance of the model.

5. Conclusion

This study studied the dynamic prediction model of financial distress in the financial sharing environment. In the beginning, the AHP and entropy weight theory were employed to determine an index system for the dynamic evaluation of financial distress in the financial sharing environment, and the weight assignment method of the evaluation indexes was given as well. Then, a PNN-based dynamic prediction model of financial distress was constructed; later, combining with experiments, correlation analysis of the first-level evaluation indexes and different types of financial distress was performed, and the results had verified that there are significant correlations between the first-level evaluation indexes extracted in this study and the different types of financial distress. At last, the model prediction results obtained under different combination ratios and before and after considering timeliness were compared and analyzed, and the model with sliding time window was proved to be effective in giving dynamic predictions on the financial distress in the financial sharing environment.

The future research will deal with the following issues: (1) exploring the theoretical method for dynamic prediction of financial stress in various financial conditions; (2) differentiating between the financial indexes of different industries and building a multi-industry financial crisis prediction model.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] S. Haider, M. Shafqat, and S. Haider, "Using influence nets in financial informatics: a case study of Pakistan," *Journal of Computing and Information Technology*, vol. 20, no. 2, pp. 113–124, 2012.

[2] L. Ogiela and M. R. Ogiela, "Cognitive informatics for new classes of economic and financial information systems," in *Proceedings of the International Conference on Advanced Software Engineering and Its Applications*, pp. 188–194, Berlin, Germany, December 2010.

[3] Z. Wang, "Financial management teaching mode based on mooc under the background of informatization," in *Proceedings of the International Conference on Application of Intelligent Systems in Multi-modal Information Analytics*, pp. 137–142, Canaria, Spain, January 2020.

[4] Z. Lin, "Research on financial informatization construction in colleges and universities under the background of "Internet+"" in *Proceedings of the the Sixth International Conference on Information Management and Technology*, pp. 1–5, Kumamoto, Japan, July 2021.

[5] H. Gao, "Under the background of digital college financial problems existing in the informatization construction and solving suggestion," in *Proceedings of the International Conference on Application of Intelligent Systems in Multi-modal Information Analytics*, pp. 16–21, Canaria Spain, January 2020.

[6] L. I. Aleshin, "Financial and technological bases as central factors in library informatization," *Scientific and Technical Information Processing*, vol. 39, no. 1, pp. 51–53, 2012.

[7] A. Y. Bystryakov and V. V. Mizintseva, "Innovation informatization for state financial control bodies," *Scientific and Technical Information Processing*, vol. 38, no. 2, pp. 69–77, 2011.

[8] E. Ariwa and K. Eseimokumoh, "Financial informatics enterprise and audit risk in developing economy," in *Proceedings of the 2008 First International Conference on the Applications of Digital Information and Web Technologies (ICADIWT)*, pp. 326–337, Wuhan, China, August 2008.

[9] Y. F. Lei and Q. T. Cheng, "Financial sharing of SMEs based on cloud service SaaS outsourcing model," in *Proceedings of the 2021 International Conference on Control and Intelligent Robotics*, pp. 607–612, Guangzhou, China, 2021.

[10] S. Jiang, "Research on big data audit based on financial sharing service model using fuzzy AHP," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 4, pp. 8237–8246, 2021.

[11] L. Li, Y. Feng, and L. Li, "Big data audit based on financial sharing service model," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 6, pp. 8997–9005, 2020.

[12] L. Wang and Y. Wang, "Supply chain financial service management system based on block chain IoT data sharing and edge computing," *Alexandria Engineering Journal*, vol. 61, no. 1, pp. 147–158, 2022.

[13] L. Xiong, “Enterprise financial shared service platform based on big Data,” *Journal of Physics: Conference Series*, vol. 1852, no. 3, Article ID 032004, 2021.
[14] M. Elias Malope and R. Naidoo, “Knowledge sharing challenges in subsidiary-to-subsidiary it infrastructure outsourcing: a case study on a financial services provider,” in *Proceedings of the Conference of the South African Institute of Computer Scientists and Information Technologists 2020*, pp. 237–243, Cape Town, South Africa, June 2020.
[15] Y. N. Zhuang, “The impact of the implementation of the financial shared service model on Haier Smart Home,” *E3S Web of Conferences*, vol. 235, 2021.
[16] W. M. Xi and K. Liu, “Construction and applied research of csloud platform for financial shared service center,” in *Proceedings of the 2021 International Conference on Public Management and Intelligent Society (PMIS)*, pp. 404–407, Cape Town, South Africa, September 2021.
[17] X. Yang, Y. Hou, and W. Zhang, “Research on performance management of financial shared service center based on cloud accounting,” in *Proceedings of the 2021 The 4th International Conference on Software Engineering and Information Management*, pp. 89–93, Washington, DC, USA, October 2021.
[18] Y. Liu, “Research on the financial shared service center in the “Internet+” era,” *IOP Conference Series: Earth and Environmental Science*, vol. 692, no. 4, Article ID 042124, 2021.
[19] Y. Zhang, “Innovation of financial shared service center based on artificial intelligence,” in *Proceedings of the International conference on Big Data Analytics for Cyber-Physical-Systems*, pp. 1110–1116, Shengyang, China, December 2019.
[20] J. Vlietland and H. Van Vliet, “Information sharing for effective IT incident resolving in IT service provider networks: a financial service case study,” *Journal of Software: Evolution and process*, vol. 27, no. 2, pp. 73–94, 2015.
[21] C. Z. Liu, H. Zafar, and Y. A. Au, “Rethinking fs-isac: an it security information sharing network model for the financial services sector,” *Communications of the Association for Information Systems*, vol. 34, no. 1, pp. 15–36, 2014.
[22] X. Chen, Q. Dai, and C. Na, “Effects of shared financial services on firm performance,” in *Proceedings of the 26th Americas Conference on Information Systems, AMCIS 2020, 2020, 26th Americas Conference on Information Systems*, Salt Lake City, UT, USA, August 2020.
[23] M. El Bannany, A. M. Khedr, M. Sreedharan, and S. Kanakkayil, “Financial distress prediction based on multilayer perceptron with parameter optimization,” *IAENG International Journal of Computer Science*, vol. 48, no. 3, pp. 1–12, 2021.
[24] J. Sun, H. Fujita, Y. Zheng, and W. Ai, “Multi-class financial distress prediction based on support vector machines integrated with the decomposition and fusion methods,” *Information Sciences*, vol. 559, pp. 153–170, 2021.
[25] F. Shen, Y. Liu, R. Wang, and W. Zhou, “A dynamic financial distress forecast model with multiple forecast results under unbalanced data environment,” *Knowledge-Based Systems*, vol. 192, Article ID 105365, 2020.
[26] A. G. Christopoulos, I. G. Dokas, P. Kalantonis, and T. Koukkou, “Investigation of financial distress with a dynamic logit based on the linkage between liquidity and profitability status of listed firms,” *Journal of the Operational Research Society*, vol. 70, no. 10, pp. 1817–1829, 2019.
[27] U. S. Mahtani and C. P. Garg, “An analysis of key factors of financial distress in airline companies in India using fuzzy AHP framework,” *Transportation Research Part A: Policy and Practice*, vol. 117, pp. 87–102, 2018.
[28] Z. Li, J. Crook, and G. Andreeva, “Dynamic prediction of financial distress using Malmquist DEA,” *Expert Systems with Applications*, vol. 80, pp. 94–106, 2017.