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*Retraction*

# Retracted: Research on Risk Measurement and Early Warning of Electronic Banking Business Based on GMDH Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] H. Zeng, "Research on Risk Measurement and Early Warning of Electronic Banking Business Based on GMDH Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 2678161, 9 pages, 2021.

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*Research Article*

# Research on Risk Measurement and Early Warning of Electronic Banking Business Based on GMDH Algorithm

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In order to deal with the problems of traditional e-banking risk measurement and early warning methods, such as low accuracy of e-banking risk measurement and longer early warning time, an e-banking risk measurement and early warning method based on the GMDH algorithm is proposed. This scheme mines the e-banking risk measurement and early warning indicators by the GMDH algorithm, and it will input the influencing factors and risk factors as independent variables into the GMDH modeling network and then input the e-banking business growth rate as the dependent variable into the GMDH modeling network which is standardized by the normative method of processing the e-banking business risk measurement and early warning index data. According to the processing results, it calculates the weight of the measurement and early warning index by the entropy method, and it constructs the e-banking risk measurement model with the genetic algorithm which can help to calculate the optimal solution of the parameters, formulate the risk measurement interval, and determine the risk in order to realize the risk warning of electronic banking business. The simulation results show that the proposed method has a higher accuracy of e-banking risk measurement and a shorter warning time.



## 1. Introduction

With the continuous internationalization of the financial industry and the continuous innovation of financial products, the banking business environment is undergoing profound changes, and its complexity and uncertainty are increasing day by day. As a result, the risks of e-banking business are more complex and destructive. The failure of any large financial institution will have a severe negative impact on the sound operation of the global financial system. In the past 20 years, e-banking business risks have induced a series of financial crises, and the results are mostly internal crises in the banking system, such as the collapse of the Bank of Barings in the United Kingdom, the Banking Crisis in Naples in Italy, the collapse of Credit Lyon Bank in France, and the Bank of Japan Daiwa. Banking crises, larger ones, are a country or a place or even an international overall crisis, such as the Mexican financial crisis at the end of 1994, the Asian financial crisis in 1997, the Russian ruble crisis in 1998, and the US subprime mortgage crisis in 2007, as well as the Wall Street financial crisis and subsequent global financial tsunami, as well as the European debt crisis caused by government credit in 2009, etc. In short, under the influence of e-banking business risks, the frequency of global financial crises is getting higher and higher, the spread is wider and wider, and the destructiveness is getting bigger and bigger [1]. Therefore, it is urgent to strengthen the understanding of the risks of e-banking business. Electronic banking is the foundation of the virtual economy. The establishment of a complete, effective, and reasonable internal control system to maintain the reasonable flow of electronic banking funds and standard operations has become an important issue in the management of electronic banking. Risk measurement is an important part of the internal control of e-banking, and it is the basis for effective internal control. Only by correctly identifying and measuring risks can internal control activities be carried out in a targeted manner. Judging from the cases of domestic and foreign bank risks in recent years, the most important and most basic thing for carrying out internal control activities is to

establish a sound risk measurement system to control the risks of e-banking business [2].

The e-banking business risk measurement index system is an important part of the continuous supervision of e-banking. It is a summary of the continuous supervision of e-banking, and it is also the basis for the implementation of control over e-banking. The e-banking business risk measurement index system is conducive to the regulatory agencies to systematically recognize the business risk issues of e-banking and take targeted regulatory measures. The comprehensive measurement results can also be used as a reference for market access approval, which is conducive to improving market standards. The scientific nature of entry approval can also provide a certain basis for e-banking to implement market exit. Therefore, we should pay more attention to comprehensive and all-round electronic banking risk measurement, absorb advanced experience in the international financial industry, and gradually improve the risk measurement system to control nonperforming assets, enhance risk resistance, improve core competitiveness, and enable electronic banking to compete and be neutral and invincible.

Literature [3] proposes a commercial bank credit risk measurement method based on BP neural network. It uses the on-balance sheet and off-balance sheet business of commercial banks as the entry point and uses the financial data of 500 credit enterprises from the local corporate bank in Guizhou Province to improve the BP neural network model. A credit risk measurement model was established by simulation, and good results were achieved. The credit risk measurement model was used to predict 49 sample companies. It was found that the model has a strong practical guiding significance for the reminder and early warning of credit risk, which is beneficial to improving the ability of commercial banks to prevent and control credit risks, which will also help the central bank to quantify differentiated monetary policies and improve the efficiency of macroprudential management. Literature [4] proposed a method for measuring the operational risk of listed commercial banks based on the Bayesian network model, collecting sample data of 323 listed commercial banks' operational loss events, and preprocessing the sample data. According to the preprocessing results, the Bayesian network model measures the operational risks of listed commercial banks in my country. The results show that the main operational loss events of listed commercial banks in my country include internal fraud, external fraud, and asset management. The business lines with the most operational loss events include retail banks and commercial banks. There are three types of banking and asset management. Most of the operational loss incidents are low-level loss incidents. Zhu et al. proposed a fault early warning approach of coal mills based on the thermodynamic law and data mining [5]. In this paper, the thermodynamic law is used to describe the working characteristics of coal mills and to determine the multiparameter vector that characterizes the operating state of the coal mill. Data mining technology is applied to analysis the interrelationships among elements of the multi-parameter vector. Then the abnormal boundaries of parameters are calculated based on the distribution of parameters under different working conditions according to the Pauta criterion. Finally, the fault early warning model is implemented combining the abnormal boundaries and the confidence algorithm that can detect the working status of coal mills. Li et al. considered the sensitivity of unstructured network data to external shocks in the financial system, based on HMM applied in the traditional financial indicator system to construct the new composite index [6]. They integrated economic statistical structure data and Internet information, to capture the internal correlation and external shocks to financial markets.

The contributions of this paper can be descripted as follows.

(1) Although the abovementioned literature have put forward some suggestions for dealing with e-banking risk measurement and early warning, the accuracy of e-banking risk measurement is low and the early warning time is longer. For this reason, this paper proposes a self-organizing data mining algorithm (GMDH)-based e-banking risk measurement and early warning method.

(2) We use this new scheme to mine the e-banking risk measurement and early warning indicators by the GMDH algorithm, and it will input the influencing factors and risk factors as independent variables into the GMDH modeling network and then input the e-banking business growth rate as the dependent variable into the GMDH modeling network which is standardized by the normative method of processing the e-banking business risk measurement and early warning index data.

This article mainly contains four sections. Section 2 presents the e-banking risk measurement and early warning methods. The results of the experiment are also presented and analyzed in Section 3. Finally, Section 4 sums up some conclusions and gives some suggestions as the future works.

## 2. E-Banking Risk Measurement and Early Warning Methods

### *2.1. E-Banking Risk Measurement and Early Warning Index Selection*

*2.1.1. GMDH Algorithm.* The GMDH algorithm can objectively and autonomously select the influencing factors that have an important effect on the research object in the iterative self-organization process. When studying complex economic systems, multiple factors in the system have mutual influences and effects, and self-organizing data mining algorithms provide an effective way to solve this problem. As the core technology of self-organizing data mining, GMDH (Group Method of Data Handling) mainly includes the following four models: parametric GMDH input and output model, parametric GMDH autoregressive model, nonparametric similar synthesis model, and nonparametric fuzzy rule induction model. Among them, the parameter GMDH input and output model can automatically select the independent variables that enter the model

and perform hierarchical screening through optimal criteria, so it is often used for the extraction and output of key variables in complex economic systems [7]. The algorithm can analyze and process the relationship between the input variables of the system, use self-organizing data mining technology to objectively and directly generate the optimal fuzzy rules from all possible fuzzy rules of the system and directly and effectively describe the fuzzy system qualitatively and quantitatively, So as to establish a predictive model. The self-organizing data mining algorithm is based on the selection program, that is, the candidate models of each layer are continuously tested according to the given external criteria [8]. Therefore, the basic idea of the GMDH modeling process is to carry out multiple self-organizing and hierarchical iterations on all the input influencing factors of the system and to screen the models according to the selected corresponding external criteria, so as to obtain the optimal complexity model. The model steps are the following.

(1) Divide the data sample set into a training set and a test set.

(2) Construct the functional relationship between the dependent variable and the independent variable. Generally, the K-G polynomial is selected as the "reference function" of the functional relationship.

(3) Select one (or more) from the selection criteria with external complement properties as the objective function (i.e., external criteria).

(4) The initial organization $v_i$ continuously self-organizes to generate the first-level intermediate model.

(5) Establish the first-level intermediate model. According to the external criteria, the intermediate model generated in the first layer is screened on the test set, and the screened intermediate model $w_k$ will be used as the input variable of the second layer of the network [9].

(6) Get the optimal complexity network structure. Repeat the third and fourth steps to generate the second layer, third layer, . . . , $N$-th layer intermediate model and finally get the optimal display complexity model we need.

The GMDH modeling process is shown in Figure 1.

*2.1.2. Selection of Metrics and Early Warning Indexes Based on GMDH Algorithm.* E-banking business risks are simultaneously affected by political, economic, cultural, social, and other factors. It is quite difficult to accurately measure and warn them. Therefore, it is necessary to establish a multilevel and comprehensive reflection of the e-banking process "several indicator groups" of the business risks that may be faced in the e-banking business, scientifically predicting the possibility, the degree of harm, and the consequences of the risks of electronic banking [10]. This article uses the GMDH algorithm to objectively and automatically dig out the e-banking risk measurement and early warning indicators.

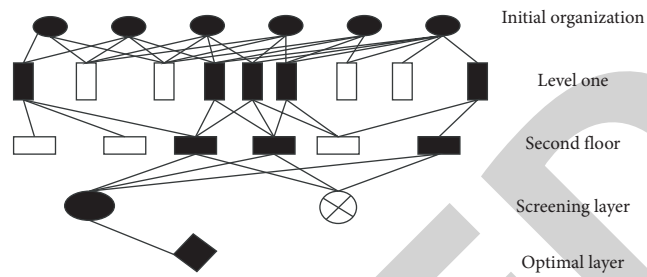


Figure 1: GMDH modeling process.

*(1) Macroeconomic Environment Indicators.* This indicator type is mainly an indicator reflecting the overall operation of the country's economic system, including the following:

(1) Economic growth rate (A1): this indicator reflects the overall macroeconomic situation faced by the surveyed object and refers to the economic growth rate of nominal GDP after deducting inflation factors, also known as the real GDP growth rate [11]. The economic growth rate calculation formula is

$$\mathrm{A1} = \frac{1+E}{1+P} \times 100\% - 1. \tag{1}$$

In the formula, $E$ represents the nominal GDP growth rate; $P$ represents the inflation rate.

(2) Inflation rate (A2): inflation rate reflects the stability of a country's currency value and is a manifestation of a country's macroeconomic stability.

(3) The unemployment rate (A3) refers to the ratio of the unemployed population to the labor population. Achieving full employment and controlling the unemployment rate within a reasonable range are conducive to enhancing the confidence of the national economy and maintaining social stability [12].

(4) Consumer price index (A4): the consumer price index is used to reflect the price changes of products and services closely related to the lives of residents. It is usually used to reflect the purchasing power of consumers and also reflect economic factors, which are business conditions.

(5) Enterprise prosperity index (A5) is a compiled index based on the judgment and expectation of the person in charge of the enterprise on the overall production and operation of the enterprise and is used to comprehensively reflect the production and operation of the enterprise. This indicator is mostly in the form of questionnaire surveys, mainly qualitative, supplemented by quantification, and the combination of qualitative and quantitative prosperity indicators is used by the system to accurately and timely reflect the macroeconomic operation and business conditions of the enterprise and to predict the changing trend of economic development [13].

*(2) Early Warning Indicators of Fiscal and Monetary Conditions*. This indicator type is mainly an indicator reflecting the state of the country's fiscal and monetary economy, including the following:

(1) The ratio of fiscal deficit to GDP (B1). This indicator measures the country's fiscal affordability. In my country, due to the close relationship between the government and the electronic banking system, the larger the fiscal deficit, the heavier the burden of electronic banking. If at the same time the GDP growth rate is not high and exports decline, then the overall economic level will decline, which will cause market confidence, which is extremely pessimistic.

(2) National debt burden ratio (B2), also known as national economic affordability, refers to the proportion of the cumulative balance of national debt in GDP. This indicator focuses on the stock of national debt and reflects the ability of the entire national economy to bear national debt.

(3) Money supply growth rate (B3): this article selects currency, transferable demand deposits, household savings deposits, and fiscal deposits as the money supply indicators.

(4) Interest rate level (B4): the interest rate level reflects the fund supply and demand situation of the whole society in a certain period of time. In terms of its manifestation, it refers to the ratio of the amount of interest to the total borrowed capital in a certain period of time [14].

(5) Exchange rate level (B5): this indicator refers to the exchange ratio between two currencies and can also be regarded as the value of one country's currency to another country's currency.

*(3) Early Warning Indicators of Financial Environment Conditions*. This indicator type is mainly an indicator reflecting the conditions of the securities market, factor market, etc., mainly including the following:

(1) The comprehensive annual $\beta$ value of the stock market (C1): when calculating the comprehensive market $\beta$ value, this paper selects the Shanghai and Shenzhen market comprehensive return rate for all stocks.

(2) Stock price-to-earnings ratio (C2): this indicator comprehensively reflects the two characteristics of investment stocks in terms of cost and income in a certain period of time. The higher the P/E ratio is, the longer it will take to recover the cost and vice versa.

(3) Fixed asset growth rate (C3): this indicator mainly reflects the growth of fixed asset investment in a certain period of time [15].

*(4) Early Warning Indicators of the Balance of Payments Status*. This indicator type is mainly an indicator reflecting the country's foreign economic situation, and its main indicators include the following:

(1) Current account (D1): this indicator refers to the flow of funds arising from trade and services in the balance of payments. The current account surplus increases a country's net foreign capital by a corresponding amount; the current account deficit is just the opposite.

(2) The ratio of short-term foreign debt to the balance of foreign debt (D2), which has the ability to measure whether a country's capital inflow is reasonable, reflects the maturity structure of a country's foreign debt. The larger the value is, the greater the repayment pressure of the country is.

(3) Debt ratio (D3) refers to the ratio of the balance of foreign debt at the end of the year to the export income of goods and services in the balance of payments statistics of the year.

(4) The proportion of external debt outflow to GDP (D4) reflectes the dependence of a country on foreign debt; the greater the index, the greater the dependence of debtor countries on debt and the weaker their resistance to the impact of international financial market and international economic environment changes.

*(5) Financial Enterprise Vulnerability Early Warning Indicators*. This indicator type mainly reflects the risk situation of financial enterprises, mainly including the following:

(1) The ratio of nonperforming loans (E1) and the balance of nonperforming loans are classified according to the five levels of loans and the sum of subprime loans, doubtful loans, and loss loans.

$$\mathrm{E1} = \frac{T}{V} \times 100\%, \tag{2}$$

where $T$ represents the balance of nonperforming loans; $V$ refers to the balance of each loan.

(2) Capital adequacy ratio (E2): the capital adequacy ratio is an indicator of the safety of commercial banks' capital. The higher the ratio, the higher the bank's robustness, which indicates the commercial bank's impact on its asset portfolio and business risks. The calculation formula of the loss compensation ability is as follows:

$$\mathrm{E2} = \frac{Z}{J + 12.5S} \times 100\%. \tag{3}$$

In the formula, $Z$ represents net capital; $J$ represents weighted assets; $12.5S$ represents 12.5 times the market risk requirement.

(3) The return on assets (E3) reflects the bank's profitability index. The larger the value is, the more profits the assets bring to the enterprise. The calculation formula is

$$\mathrm{E3} = \frac{g}{P} \times 100\%. \tag{4}$$

In the formula, $g$ represents net profit; $P$ represents the average balance of assets.

(4) Liquidity ratio (E4): this indicator is a measure of the financial security status and solvency of electronic banks. The higher the indicator ratio, the stronger the company's ability to repay short-term debts, but not the higher the better. The calculation formula is

$$\mathrm{E4} = \frac{L}{F} \times 100\%. \tag{5}$$

In the formula, $L$ represents liquid assets and $F$ represents liquid liabilities.

(5) Loan-to-deposit ratio (E5): this indicator is a measure of the liquidity risk of e-banking. This indicator is a moderate indicator. Too high a loan-to-deposit ratio may lead to a bank's payment crisis, but if it is too low, it indicates the bank's profitability is poor. In my country, it is stipulated that the loan-to-deposit ratio of electronic banks should be less than or equal to 75%. The calculation formula is

$$\mathrm{E5} = \frac{G}{M} \times 100\%. \tag{6}$$

In the formula, $G$ represents the sum of various loans and $M$ represents the sum of various deposits.

*2.2. Index Data Preprocessing.* The above influencing factors and risk factors are input into the GMDH modeling network as independent variables, and the e-banking business growth rate (GR) is input into the GMDH modeling network as dependent variables. However, when GMDH is modeled, the e-banking risk measurement and early warning indicators obtained above are affected by the dimensions between different indicators, which makes it impossible to compare indicators of different units and different directions. Therefore, the standardized processing of e-banking risk measurement and early warning index data through the normative law has improved the accuracy of e-banking risk measurement and early warning, thereby laying the foundation for subsequent e-banking risk measurement and early warning. Since the above indicators can be divided into two types, benefit type and cost type, the two types of indicator data are processed separately.

For benefit-oriented indicators,

$$X_{ik} = \frac{X'_{ik}}{\max X'_{ik} + \min X'_{ik}}, \tag{7}$$

where $X_{ik}$ is the revised value and $X'_{ik}$ represents the original data.

For cost indicators,

$$X_{ik} = 1 - \frac{X'_{ik}}{\max X'_{ik} + \min X'_{ik}}. \tag{8}$$

*2.3. Index Weight Calculation.* E-banking risk measurement and early warning index weight refers to the degree of influence of e-banking risk measurement and early warning indicators on the e-banking risk measurement and early warning effect. It is determined by the value of the banking risk measurement and early warning effect and the banking risk measurement and early warning targets are determined by public review. Therefore, after preprocessing the banking risk measurement and early warning indicator data, the entropy method is used to calculate the weight of the measurement and early warning indicators, which can eliminate the influence of subjective factors on the measurement and early warning results to a certain extent, making the measurement and early warning results more objective. Use the entropy method to calculate the weights of metrics and early warning indicators. The steps are as follows:

(1) First construct m judgment matrix $R$ consisting of $Am$ metrics and early warning objects and $n$ metrics and early warning indicators:

$$o = \left(r_{ij}\right)_{mn} X_{ik}, \tag{9}$$

where $X_{ik}$ is the revised value, $r_{ij}$ is a number of $R$, and $o$ is $n$ metrics and early warning indicators value.

(2) Normalize the judgment matrix $o$ to obtain the processed matrix B. The elements of B are

$$b_{ij} = \frac{r_{ij} - r_{\min}}{r_{\max} - r_{\min}}. \tag{10}$$

In the formula, $r_{\max}$ represents the most satisfactory object when the metric and the early warning indicator are the same and $r_{\min}$ represents the least satisfactory object under the same indicator.

(3) Use the entropy method to calculate the weights of metrics and early warning indicators:

$$W = \frac{1 - H_i}{n - \sum_{i=1}^{n} H_i}. \tag{11}$$

According to the above formula, we can see that the smaller the entropy value of the e-banking business risk measurement and early warning indicator, the larger the corresponding entropy weight, which indicates that the importance of the measurement and early warning indicator is related to the effectiveness of the amount of information it carries. In other words, the smaller the entropy value of the measurement and early warning index, the more effective the information it carries and the more important the measurement and early warning index. It can be seen that entropy weight is not affected by the subjective factors of measurement and early warning and directly reflects the importance of the information carried by the measurement and early warning indicators. Therefore, the weight of the measurement and early warning indicators obtained through the entropy method is objective.

*2.4. E-Banking Risk Measurement Model.* Based on the weights of the metrics and early warning indicators obtained above, a risk measurement model for e-banking business is built to provide support for risk measurement.

Construct a basic model of e-banking business risk measurement, and its expression is

$$R = F(V, T, C). \tag{12}$$

In the formula, $R$ represents the risk of electronic banking business; $C$ represents the existing electronic banking business risk control measures; $V$ represents the efficiency of electronic banking business processing; and $T$ represents the risk control cycle.

From the perspective of the risk defined by ISO/IEC, it can be expressed by the vulnerability of the threat, the severity of the possibility, etc.; then formula (13) can be expressed as

$$R = F(Pt, Pv, V). \tag{13}$$

In the formula, $Pt$ represents the probability of threat and $Pv$ represents the severity of vulnerability.

Set the probability of occurrence of threat $Pt$ to be in the range of $[0, 1]$, reflecting the possibility of occurrence of a risk event. The closer the probability of threat occurrence is to 1, the greater the possibility of e-banking risk events is; conversely and the less likely it is that e-banking risk events will occur.

The severity of vulnerability $Pv$ exists objectively, but only when the threat is exploited will it bring risks to the e-banking business. The greater the severity of vulnerability, the greater the risk of e-banking business.

The effectiveness of risk control measures also determines the possibility of e-banking risk events, which affects the accuracy of risk measurement. The greater the effectiveness of risk control measures, the smaller the risk of e-banking business. The formula for calculating the effectiveness of risk control measures is

$$\mathrm{Sm} = 1 - \frac{Nv}{NR}. \tag{14}$$

In the formula, $Nv$ represents the number of occurrences of electronic banking risks and $N$ represents the total number of threats to electronic banking.

According to the above formula, the Poisson distribution is used to quantify the risk measurement index, combined with formula (14) to obtain the e-banking risk measurement model as

$$\begin{cases} Q = \sum_{k=1}^{k}\left(V \times \dfrac{e^{-\lambda}\lambda^{x}}{Sm} \times Pv\right), & k < 10, \\ Q = \sum_{k=1}^{k}\left(V \times \dfrac{1}{\sqrt{2\pi\lambda}} e^{(n-\lambda)^2/2\lambda} \times Pv\right), & k \geq 10. \end{cases} \tag{15}$$

*2.5. E-Banking Risk Warning.* Based on the e-banking risk measurement model constructed above, the genetic algorithm is used to calculate the optimal solution of the parameters, the risk measurement interval is established, and the degree of risk is determined, thereby realizing the early warning of the e-banking business risk.

It is known from formula (15) that the values of $Q$ and $k$ need to be taken, and the specific solution process is as follows.

Set the initial population as $\mathrm{Chrom} = \{(Rt1, k1), \ldots, (Rti, ki), \ldots, (Rt20, k20)\}$, where $Rti$ and $ki$, respectively, represent the real number values within the range of $Rt$ and $k$.

Calculate the fitness of individual population; the expression is

$$\text{fitness} = \left|V_j - V_i\right|. \tag{16}$$

Among them, $V_j$ represents the fitness value of the population and $V_i$ represents the expert evaluation value.

The smaller the value of fitness, the greater the chance that the individual will be retained in the new generation population. According to the calculation result of formula (16), the optimal individual is obtained through selection, crossover, and mutation operations, and the corresponding value is the optimal solution of the model parameters. Substituting formula (15) to obtain the optimal e-banking risk measurement model, the sample data is input into the model to obtain the e-banking business risk measurement value. Based on this, the risk level is determined, and the e-banking business risk early warning is carried out according to the risk level. The risk level determination is shown in Table 1.

## 3. Simulation Experiment Analysis

In order to verify the effectiveness of the e-banking risk measurement and early warning method based on the GMDH algorithm proposed in this paper in practical applications, Matlab simulation software is used for simulation experiment analysis. Obtain e-banking business risk measurement and early warning indicators through the e-banking database, as shown in Table 2.

According to the obtained indicators, a comparative analysis of the e-banking risk measurement accuracy of the method in this paper, the method in literature [5], and the method in literature [6] is carried out, and the comparison result is shown in Figure 2.

According to Figure 2, the accuracy of the e-banking business risk measurement of the method in this paper is up to 100%, which is higher than the e-banking business risk measurement accuracy of the method in literature [5] and the method in literature [6], which shows that the method in this paper is used in e-banking risk measurement. The accuracy of the e-banking business risk measurement of the method in reference is up to 60% in [6], which is 55% in [6]. In addition, the performance of accuracy almost linearly increases, which has the best performance.

In order to further verify the effectiveness of the method in this paper, a comparative analysis of the e-banking risk

Table 1: Rules for determining the degree of risk.

| Degree of risk | Risk measure | Description |
|---|---|---|
| No risk | [0, 60] | E-banking business is normal and there is no possibility of risk |
| Low risk | [60, 75] | E-banking business is basically stable, and there is a possibility of risk |
| Medium risk | [75, 90] | E-banking business conditions fluctuate, and there is a possibility of obvious risks |
| High risk | [90, 100] | Deterioration of e-banking business, risks may occur |

Table 2: E-banking risk measurement and early warning indicators.

| Indicator type | Indicator name |
|---|---|
| Macroeconomic environment (A) | Economic growth rate (A1)<br>Inflation rate (A2)<br>Unemployment rate (A3)<br>Consumer price index (A4)<br>Business climate index (A5) |
| Fiscal and monetary status (B) | Fiscal deficit to GDP ratio (B1)<br>National debt burden ratio (B2)<br>Money supply growth rate (B3)<br>Interest rate level (B4)<br>Exchange rate level (B5) |
| Financial environment (C) | Stock market comprehensive market annual $\beta$ value (C1)<br>Stock price-earnings ratio (C2)<br>Fixed asset growth rate (C3) |
| Balance of payments (D) | Current account (D1)<br>Short-term foreign debt in total foreign debt (D2)<br>Debt ratio (D3)<br>External debt outflow as a percentage of GDP (D4) |
| Vulnerability of financial institutions (E) | Nonperforming loan ratio (E1)<br>Capital adequacy ratio (E2)<br>Return on assets (E3)<br>Liquidity ratio (E4)<br>Loan-to-deposit ratio (E5) |

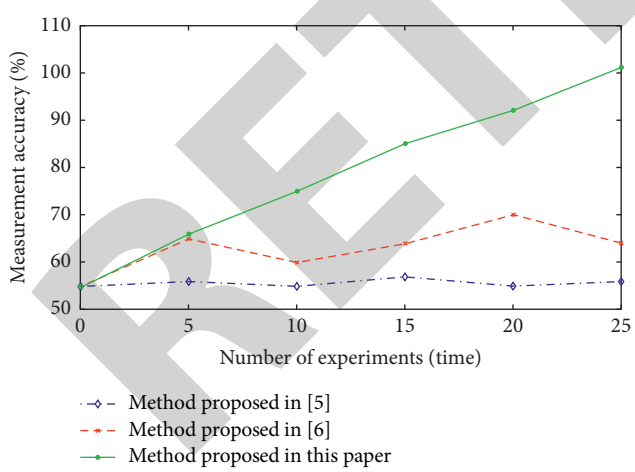


Figure 2: Comparison results of the measurement accuracy of the three methods.

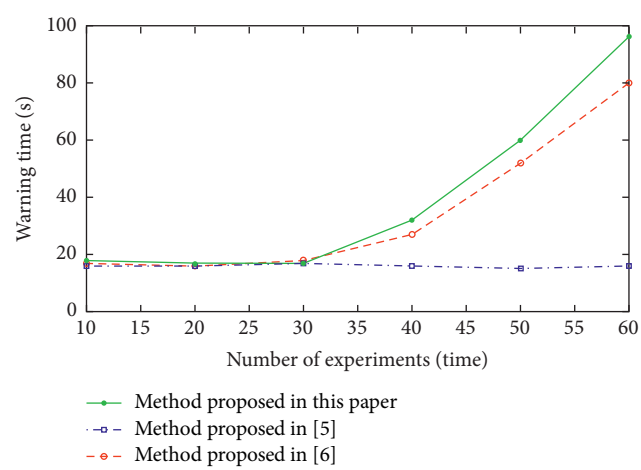


Figure 3: Comparison results of the early warning time of the three methods.

warning time of the method in this paper, the method in literature [5], and the method in literature [6] is carried out. The comparison result is shown in Figure 3.

According to Figure 3, the warning time of these three methods is almost the same when $0 < t < 30$; however, when $t > 30$, it almost linearly increases. So we can draw that it can be seen that the time cost of using the method of this paper to carry out the risk warning of electronic banking is shorter than that of the method of literature [5] and the method of literature [6], indicating that the method of this paper has a stronger early warning capability.

## 4. Conclusion

Compared with the grim reality, although researchers have noticed the relationship between e-banking business risks and financial crises and have conducted certain studies on e-banking business risks, the systematic measurement of e-banking business risks is still weak. The depth and pertinence of the analysis are not strong yet. Electronic banking is the core of the financial system. Under the background of global economic integration, financial model liberalization, and financial product innovation, electronic banking is in an extremely unstable environment, and its business risks are more objective and contagious, which are acceleration, concealment, uncertainty, and great destructiveness. Therefore, the effective identification and measurement of the risks faced by electronic banking, especially the systemic risks that cannot be dispersed through effective means, and the establishment of a comprehensive and active early warning and prevention mechanism have practical significance not only for electronic banking but also for improving electronic banking. The operating efficiency of banks and the enhancement of market competitiveness, the promotion of the integration of electronic banking with international commercial banks, the improvement of the electronic banking market, and the guarantee of national economic security are all of very important theoretical value and practical significance.

This paper proposes a self-organizing data mining algorithm (GMDH)-based e-banking risk measurement and early warning method. It can mine the e-banking risk measurement and early warning indicators by the GMDH algorithm, and it will input the influencing factors and risk factors as independent variables into the GMDH modeling network and then input the e-banking business growth rate as the dependent variable into the GMDH modeling network which is standardized by the normative method of processing the e-banking business risk measurement and early warning index data.

According to the above description, this paper proposes a new scheme to deal with the risk measurement and early warning of electronic banking business based on GMDH algorithm. In this paper, this new strategy can deal with the problems of traditional e-banking risk measurement and early warning methods, such as low accuracy of e-banking risk measurement and longer early warning time, an e-banking risk measurement, and early warning method based on the GMDH algorithm. As mentioned above, this scheme mines the e-banking risk measurement and early warning indicators by the GMDH algorithm, and it will input the influencing factors and risk factors as independent variables into the GMDH modeling network and then input the e-banking business growth rate as the dependent variable into the GMDH modeling network which is standardized by the normative method of processing the e-banking business risk measurement and early warning index data. Although this new strategy is demonstrated to be very useful, there is still much room to be improved, such as the time complexity of the algorithm that needs to be further reduced. In the future, we will try to introduce the artificial intelligence in this field and further improve the performance.

## Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Conflicts of Interest

The author declares that he has no conflicts of interest.

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