Mobile payment risk prediction of communication operators under new business model

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Abstract: In order to overcome the problems of low precision and high energy consumption existing in traditional methods, this paper studies the risk prediction of mobile payment of communication operators under the new business model. In this paper, the expert evaluation method is used to establish the mobile payment risk prediction index system of communication operators under the new business model. The analytic hierarchy process is used to calculate the weight of the prediction index through the structure of hierarchy, the construction of judgment matrix, the calculation of weight vector, the consistency test and the calculation of combined weight vector. The fuzzy comprehensive evaluation method is used to build the mobile payment risk prediction model. The prediction accuracy of the proposed method is always higher than 97%, the total CPU consumption is 34.64%, and the memory utilisation is 12.36%, which has high prediction accuracy and low prediction energy consumption.

Keywords: new business model; communication operator; mobile payment risk; prediction model.

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1 Introduction

With the emergence of new business model, the cooperation and docking between major telecommunication operators and commercial banks has opened a window for the development of Internet finance in China. In this context, with the assistance of mobile electronic devices, mobile payment methods quickly swept the country. So far, mobile payment has become the main mode of payment in China. The emergence of mobile payment makes consumption more flexible and convenient, shortens transaction time, eliminates distance and geographical constraints, avoids counterfeit currencies and errors, improves the network trading environment, and promotes economic circulation. In addition, more importantly, with mobile payment as the medium, operators integrate all kinds of information such as mobile communication card, bus card, subway card, bank card and so on, which greatly facilitates people's daily life (Pal et al., 2017). However, with the prosperity and development of mobile payment, the security risk problem is becoming more and more serious, which is threatened by mobile virus, network fraud, malicious code, privacy theft and other aspects. As a result, two-dimensional code and network fraud events continue to occur, and the amount of loss to consumers continues to rise. According to the survey of China UnionPay, in 2018, the per capita loss of consumers increased from about 1,600 yuan in 2017 to about 1,800 yuan. Among them, actively installing unknown files from mobile phones or scanning unknown two-dimensional codes have become one of the main risks faced by mobile payment, with the actual loss rate as high as 95% (Sung et al., 2017). Under this background, how to ensure the security of mobile payment is one of the most important issues in today's society. After research, the only way out for mobile payment security is to find and identify the risks of mobile payment in time and adopt corresponding solutions to remedy them. Therefore, it is of great practical significance to predict the risk of mobile payment.

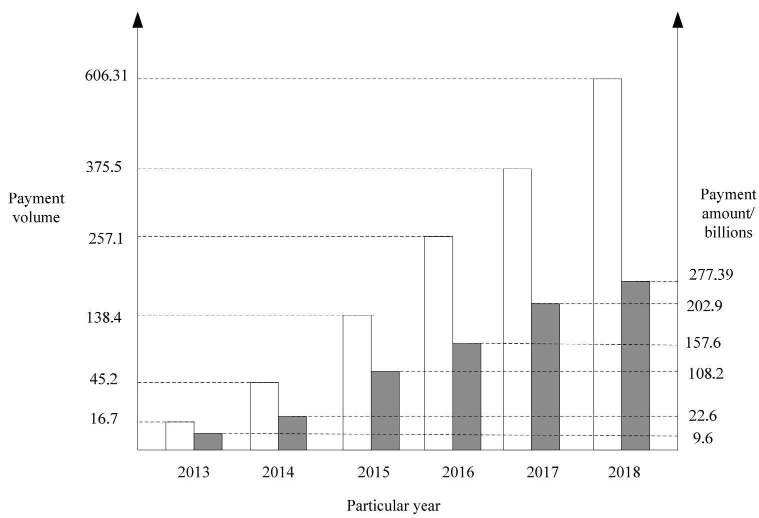
At present, in order to solve the problem of mobile payment risk, many predicting methods have been put forward by domestic and foreign experts. Kang and Nyang (2017) propose a risk prediction method for mobile payment of telecommunication operators based on analytic hierarchy process (AHP). This method summarises the individuality and difficult security problems of mobile payment relative to Internet payment, and constructs the risk prediction indicator structure of mobile payment by Delphi method. AHP is used to calculate the weight of each indicator, find out the risk nodes in the indicator system designed, and realise the risk prediction of mobile payment for telecommunication operators. However, this method has the problem of low prediction accuracy in the application process. Makki et al. (2016) propose a risk prediction method for mobile payment of telecommunication operators based on LSTM neural network. LSTM neural network's self-learning, self-organising adaptability and strong fault-tolerant pair are used to evaluate the mobile payment risk. The predicted results are verified in logistic regression classifier, and the classifier is tested with confusion matrix. However, the method has the problem of high energy consumption in prediction, and the practical application effect is not satisfactory. Yohan et al. (2018) propose a risk prediction method for mobile payment of telecommunication operators based on convolutional neural network. Firstly, the input data is divided into dynamic data and static data, and the dynamic data and static data are transformed into matrices and vectors respectively. Then, the improved convolutional neural network is used to extract features automatically and classify them. Finally, ROC curve, AUC value and KS value are used as evaluation indicators to realise the mobile payment risk prediction of telecommunication operators. However, this method has the problems of low accuracy and high energy consumption in the application process. Xia et al. (2017) propose a risk prediction method for mobile payment of telecommunication operators based on improved Apriori algorithm. Firstly, through the analysis of the composition characteristics of the risk, the risk database is established, the relevant information of the risk database is extracted, the Apriori algorithm is applied to deal with it, and the occurrence law of the risk is found by finding out the correlation of the risk occurrence. The improved candidate extraction method is used to reduce the spatial complexity of Apriori algorithm and improve the operational efficiency. By analysing the calculation results of Apriori algorithm, discovering the association rules between risk events and risk results, the mining results are analysed, to complete the risk prediction of mobile payment for telecommunication operators. But this method has the problem of high energy consumption in practical application.

Because the traditional method does not take into account the impact of business model on mobile payment risk prediction of telecommunication operators in the design process, there are problems of low prediction accuracy and high energy consumption. In order to solve the problems existing in the traditional method, a more effective method for mobile payment risk prediction of telecommunication operators in the new business model is studied.

2 Predictive analysis of mobile payment risk of communication operators under new business model

Since 2013, with the promotion of the third-party mobile payment platform such as Alipay and WeChat payment, the Mobile payment market in China has experienced explosive growth (Khalilzadeh et al., 2017). According to the data of China Payment and Settlement Association, in 2018, China Mobile paid 60.531 billion units, amounting to 27.739 billion yuan, with an increase of 61.19% and 36.69% over the same period of last year, respectively, as shown in Figure 1.

Figure 1 Size and growth of mobile payment market in China



Influenced by mobile virus, network fraud, malicious code, privacy theft and other unsafe factors, mobile payment process has great risks, so it is of great practical significance to avoid property losses for users and to predict the risks in the process (Levy et al., 2018; Angelo and Stefano, 2016; Cheung and Wong, 2017). In this study, the AHP and grey relational degree are applied. Firstly, AHP is used to select model indicators, construct indicator system and calculate indicator weight. Then, based on the fuzzy comprehensive evaluation method, a prediction model is established to predict the mobile payment risk of telecommunication operators under the new business model.

3 Construction of risk prediction model for mobile payment under new business model

3.1 Establish the risk prediction index system of mobile payment under new business model

The purpose of establishing the prediction index system is to lay the foundation for the realisation of mobile payment risk prediction, and to be able to define the level of each prediction index, and to be able to verify and evaluate through the experimental results. Before establishing the prediction indicator system, it is necessary to select the model indicator, which is the basis of the subsequent prediction model. According to previous surveys, risk factors include mobile network security risk, credit risk, technical operation risk, financial risk and legal risk (Yang et al., 2017; Slover et al., 2017). Under the above-mentioned large indicators, it is divided into several small indicators. Each indicator reflects part of the information of the research object in varying degrees, and there is a certain correlation between them. Therefore, the performance of some indicators will overlap and it is necessary to select the indicators with high frequency and great significance from this huge set of indicators (Abbott et al., 2017). The basic idea of selecting expert evaluation method here is as follows: first, the questionnaire is formulated and sent to industry experts, and then the experts score these indicators according to the risk assessment criteria, and get the importance of indicators. Finally, the indicators are arranged in order from big to small, and several indicators with higher scores are selected. The specific process is shown in Figure 2.

After the indicator is selected by expert evaluation method, because each indicator unit is different, there are different dimensions, and different dimensions will reduce the convergence speed and accuracy of the model. Before data analysis, we usually need to standardise the data, that is, to remove the differences between different units of data, and convert them into dimensionless pure values, so that different data can be compared and weighted (Wong and Kim, 2016). Data standardisation refers to the linear transformation of the original data to map it to the interval [0, 1] (Santos et al., 2017). There are two most commonly used methods: min-max standardisation and z-score standardisation. The formulas are as follows.

The min-max standardisation is:

$$x' = \frac{x - \min x}{\max x - \min x} \tag{1}$$

where max$x$ is the maximum value of sample data and min$x$ is the minimum value of sample data.

The z-score standardisation is:

$$x' = \frac{(x - \mu)}{\sigma} \tag{2}$$

where μ is the mean of all sample data and σ is the standard deviation of all sample data.

Under the above steps, five first-level indicators and several second-level indicators are selected as the risk prediction indicators of mobile payment, and then an indicator system of the model is established. The results are shown in Table 1.

Figure 2 The basic process of establishing indicator system of forecasting model by expert evaluation method

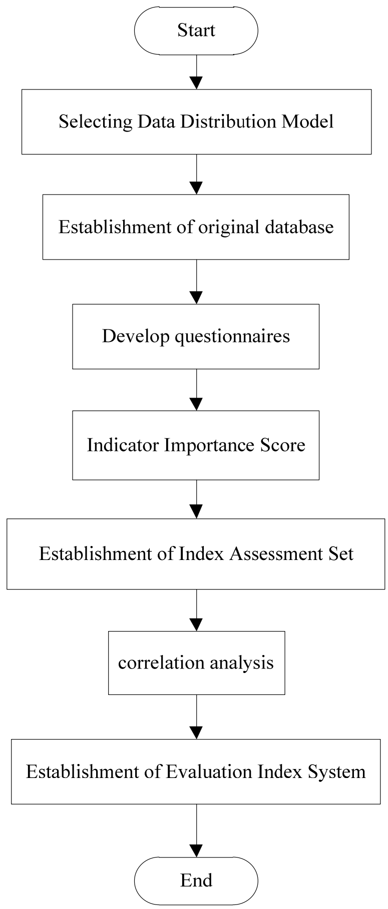


Table 1 Indicator system of the model

Forecast object	*First-level indicators*	*Secondary indicators*
Mobile payment risk of communication operators (U)	Network security risk (U1)	Risk of website tampering (U11)
		Fishing risk (U12)
		Hanging risk (U13)
		Backdoor risk (U14)
	Credit risks (U2)	Buyer's default risk (U21)
		Seller's default risk (U22)
		Payment default risk (U23)

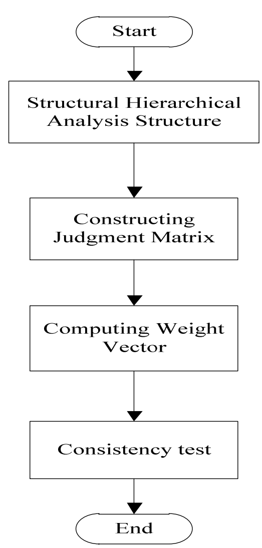
Table 1 Indicator system of the model (continued)

Forecast object	*First-level indicators*	*Secondary indicators*
		Bank default risk (U24)
	Technology and operational risk (U3)	Technical risk (U31)
		Operational risk (U32)
	financial risk (U4)	Sedimentary fund risk(U41)
		Risk of money laundering (U42)
		Cash risk (U43)
		Gambling risk (U44)
	Legal risk (U5)	Policy risk (U51)
		Legal liability risk (U52)

3.2 Indicator weight calculated by AHP

Indicator weight refers to the value and relative importance of each indicator in the whole and the magnitude of its proportion. The larger the indicator weight is, the greater the value of the indicator is, and the more important the indicator weight is. Therefore, the greater the indicator weight is assigned. The calculation of indicator weight is a key step in the construction of prediction model. The existing methods include expert scoring method, survey and statistics method, sequence synthesis method, formula method, mathematical statistics method, AHP, complexity analysis method and so on Kerviler et al. (2016). In this study, AHP is chosen to calculate the indicator weight. Its basic idea is to decompose a large multi-objective decision-making problem into multiple levels of small problems, and then gradually reach the goal in a progressive way. Now it is applied to the indicator weight calculation of the model. The specific process is shown in Figure 3.

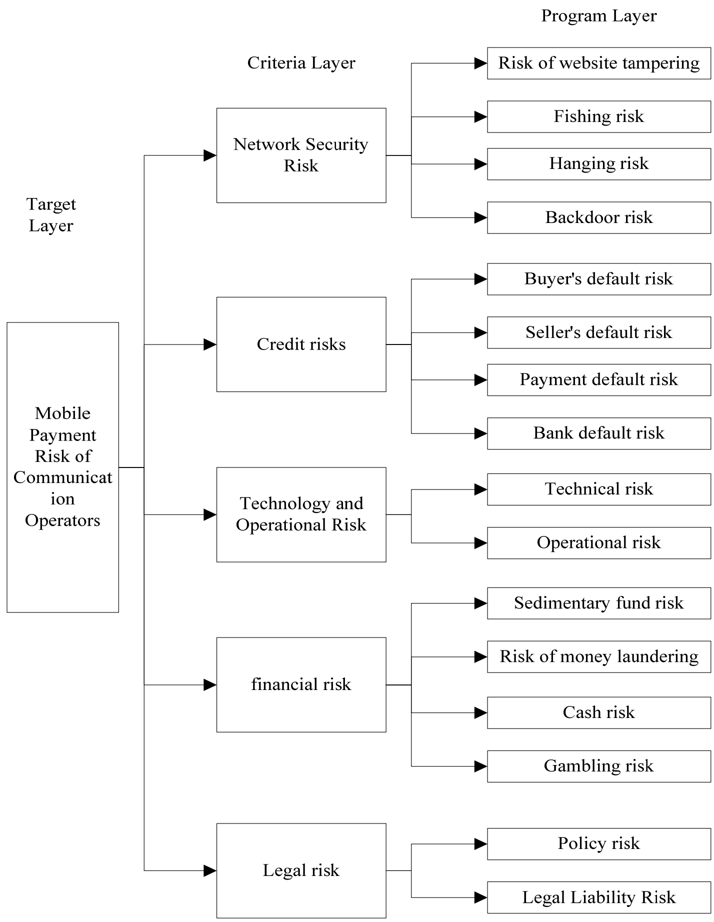
Figure 3 The process of calculating indicator weight by AHP



3.2.1 Construction of analytical hierarchy structure

The objectives, factors and objects of decision-making are divided into target level, criterion level and scheme level according to their interrelationship. The hierarchical analysis structure is drawn with the above indicator system, as shown in Figure 4.

Figure 4 Hierarchical analysis structure



In the hierarchical analysis structure, the top level is the target layer, which is used to describe the problem to be solved; the middle level is the criterion layer, which mainly includes measures to achieve the target layer; and the bottom level is the scheme layer, which is the alternative solution to solve the problem (Roy et al., 2017).

3.2.2 Construction of judgment matrix

The hierarchical analysis structure is a multi-level hierarchical structure, so starting from the second level, the relative importance of two indicators in the same level is compared. The matrix formula written according to this relative importance is the so-called judgment matrix, which is the basis of weight calculation. Starting from the second level, the same level of factors subordinate to each factor of the upper level is compared. Delphi method is used to assign the index, and then pairwise judgment matrices are constructed to the lowest level (Wu et al., 2017). In this paper, 1–9 scale method (see Table 2) is used to quantify the relative importance of each indicator, that is, the importance of each evaluation indicator is compared in pairwise way, and a judgment matrix is constructed accordingly.

Table 2 1–9 scaling method

Scale U_{ij}	*Meaning*
1	Indicator i is as important as indicator j
3	Indicator i is slightly more important than indicator j
5	Indicator i is obviously more important than indicator j
7	Indicator i is intensely more important than indicator j.
9	Indicator i is extremely important than indicator j
2/4/6/8	The intermediate value of two neighbouring judgements

Note: U_{ij} indicates the relative importance of indicator I to indicator J.

The judgment matrix model is as follows:

Table 3 Judgment matrix

U	U_1	U_2	......	U_n
U_1	a_{11}	a_{12}	......	a_{1n}
U_2	a_{21}	a_{22}	......	a_{2n}
......	......	......	......	......
U_n	a_{n1}	a_{n2}	......	a_{nn}

3.2.3 *Calculation of single-level weight (hierarchical single-ranking)*

Single-level weight refers to the importance of factors at the same level. There are many ways to calculate the importance of factors at different levels. After comprehensive consideration, the square root method is used here to calculate the weight vector. The formula is as follows:

The product T of each indicator line in the judgment matrix is calculated:

$$\mathrm{T} = \prod_{i=1}^{j} a_{ij} \tag{3}$$

The product is made *r* power as:

$$\overline{w}_i = \sqrt[r]{T_i} \tag{4}$$

Normalisation of vector $\overline{w}_i$ is as:

$$w_i = \frac{\overline{w}_i}{\sum \overline{w}_i} \tag{5}$$

The maximum eigenvalue $\psi_{\max}$ of judgment matrix A is obtained.

$$\psi_{\max} = \sum_{i=1}^{n} \frac{Aw_i}{nw_i} \tag{6}$$

3.2.4 Consistency test

The judgment matrix composed of pairwise comparisons of indicators has certain subjectivity, so consistency test is needed to ensure the accuracy of weight calculation. In this paper, consistency test needs to introduce consistency indicator, random consistency indicator and consistency ratio, which are described by mathematical formula as follows:

$$CR = \frac{CI}{RI} \tag{7}$$

where

$$CI = \frac{(\psi_{\max} - n)}{(n-1)} \tag{8}$$

In the formula, *CI* is the consistency indicator and *RI* is the random consistency indicator, as shown in Table 4. *CR* is a random consistency ratio. The closer the *CR* value is, the higher the consistency of the judgment matrix will be. When *CR* value is less than 0.1, the judgment matrix will pass the consistency test. Otherwise, the judgment matrix needs to be reconstructed until it passes the test.

Table 4 Random consistency indicator *RI*

n	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
RI	0	0.03	0.58	0.9	1.12	1.24	1.32	1.41	1.45

At this time, according to the judgment matrix passed the consistency test, the single-layer weight vector of matrix A can be obtained as follows:

$$w^u = \left(w_1^u, w_2^u, ..., w_n^u\right) \tag{9}$$

3.2.5 Computing combination weight vectors (hierarchical total sorting)

As the above-mentioned hierarchical analysis structure is divided into three layers, the relative importance of the criterion layer and the scheme layer to the target layer is combination weight vector, also known as the hierarchical total ranking (Luo et al., 2016). Next, the relative importance of the scheme layer to the overall objective is taken as an example to calculate the combined weight vector.

It is assumed that the order of *m* indicators in the scheme layer to the k^{th} factor U_k in the criterion layer is as follows:

$$\left(w_{1k}^u, w_{3k}^u, ..., w_{mk}^u\right)^T \tag{10}$$

Then the total ranking of the s^{th} indicator in the scheme layer to the target layer is as follows:

$$w_s = \sum_{k=1}^{d} \left(w_k^U \times w_{sk}^U \right),\ f = 1, 2, ..., m;\ g = f = 1, 2, ..., d \tag{11}$$

At this time, the total ranking of the scheme layer to the target layer is as follows:

$$w = \left(w_1, w_2, ..., w_m \right)^T \tag{12}$$

After calculating the combination weight vector, the consistency test needs to be done again. The test process refers to Section 1.3.4.

3.3 Construction of mobile payment risk prediction model for communication operators based on fuzzy comprehensive evaluation

The fuzzy comprehensive evaluation method is based on the development of fuzzy mathematics, and its overall idea is to make an overall evaluation of things or objects restricted by various factors by using fuzzy mathematics (Zhan and Qiao, 2016). Fuzzy comprehensive evaluation method is a comprehensive evaluation method based on fuzzy mathematics. According to the membership degree theory of fuzzy mathematics, this comprehensive evaluation method transforms the qualitative evaluation into the quantitative evaluation, that is to say, fuzzy mathematics is used to make an overall evaluation on the things or objects restricted by various factors. It has the characteristics of clear results and strong systematisation. It can solve fuzzy and hard to quantify problems, and it is suitable for solving various uncertain problems. Therefore, this method is used in the construction of risk prediction model. The flow is shown in Figure 5.

1 Construction of evaluation factor set: according to the calculation results of combined weight vector, construction of evaluation factor set x_i (i = 1, 2, …, n), and divide the evaluation factor set x_i with n vectors into c fuzzy groups, find out the clustering centre of each group, and determine the degree of belonging to each group by determining the membership.

2 Construction of evaluation index weight set: the construction of evaluation index weight set needs to adapt to the fuzzy division. On this basis, the construction of evaluation index weight set is expressed as follows:

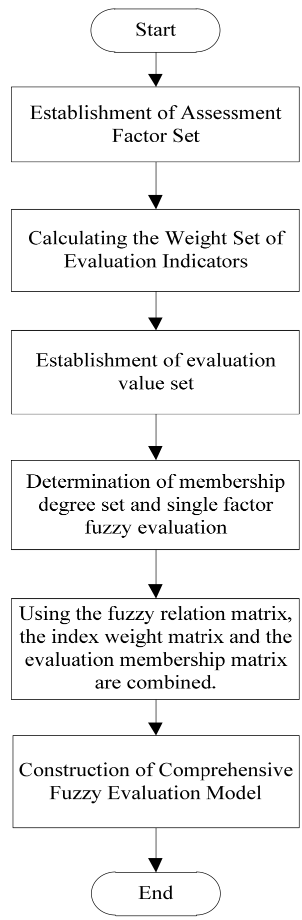
$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, ..., n \tag{13}$$

3 Construction of evaluation value set: use the fuzzy c-means algorithm to divide the evaluation indexes into several levels of fuzzy sets, regard the fuzzy levels with different data attributes as the attributes of the new data set, and form a new evaluation value set according to the levels of the original data set and the fuzzy set, which is expressed as follows:

$$J\left(U, c_1, ..., c_c\right) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j}^{n} u_{ij}^m d_{ij}^2 \tag{14}$$

In the above formula, the cluster centre of fuzzy group I is c_i, the Euclidean distance between the j^{th} data point and the i^{th} cluster centre is $d_{ij} = \|c_i - x_j\|$, and the weighted index is $m \in [1\ \infty)$.

Figure 5 Prediction model based on fuzzy comprehensive evaluation



4 Scan the new data set, then calculate the membership degree, build the membership degree set, and make a single factor fuzzy evaluation on the set. The objective function is expressed as follows:

$$\left(\sum_{i=1}^{c} u_{ij} - 1\right) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} u_{ij} - 1\right) \tag{15}$$

5 Based on the fuzzy relation matrix, the index weight matrix and the evaluation membership matrix are combined to build a mobile payment risk prediction model for communication operators, which are expressed as follows:

$$Q = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2(m-1)}} \tag{16}$$

Among them, the input of the model is the experimental sample data, and the output of the model is the mobile payment risk prediction results of the communication operators.

To sum up, through the construction of mobile payment risk prediction model of communication operators, the research on mobile payment risk prediction of communication operators under the new business model is completed.

4 Experimental test and analysis

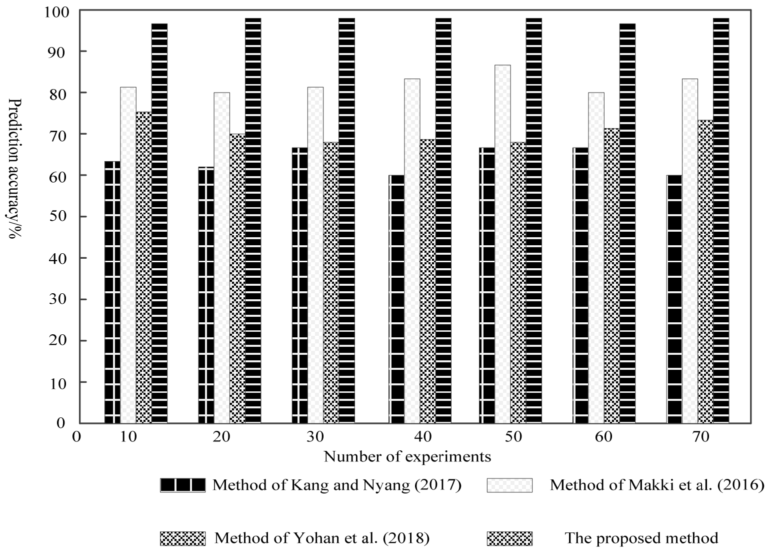
In order to verify the practical application effect of mobile payment risk prediction of telecommunication operators under the proposed new business model, a test must be carried out. The overall experimental scheme is as follows:

- Experimental environment: take a third-party mobile payment platform of a communication operator as an example to test the experiment. Test tools: under the development environment of windows & + JRE, four kinds of mobile payment security risk prediction systems are designed and implemented by using eclipse + MySQL + Tomcat development tools, thus providing a convenient and user-friendly evaluation tool for evaluators. CPU model E5500, main frequency 2.8GhZ, memory 8GB, simulation software MATLAB 7.0, operating system Windows 10.
- Experimental data: Based on the risk data of the third-party mobile payment platform of communication operators in the past three years, this paper forecasts the subsequent payment risk and compares it with the real results. The design principle of sample data length is that the data can run smoothly on the simulation platform to support this experiment. The sample data is sorted according to the time sequence, and the experiment data with the highest time is selected as the initial sample data.
- Evaluation criteria: Kang and Nyang (2017), Makki et al. (2016) and Yohan et al. (2018) methods are used as experimental comparison methods. Firstly, the accuracy of risk prediction of different research methods is compared. The higher the accuracy, the more accurate the method can realise the accurate prediction of mobile payment risk of communication operators. Furthermore, the prediction energy consumption of different research methods is tested, the lower the prediction energy consumption, indicating that the method is in progress The number of resources consumed by mobile payment risk prediction of communication operators is less. The specific experimental process is as follows:

  1 Comparison of prediction accuracy:

  In order to verify the prediction accuracy of different research methods in mobile payment risk prediction of communication operators, it is necessary to test the results as follows:

Figure 6 Comparison of prediction accuracy of different methods



From the analysis of Figure 6, it can be seen that the prediction accuracy of Kang and Nyang (2017) method varies from 61% to 77%, which is the lowest among the four methods. The prediction accuracy of Makki et al. (2016) method varies from 80% to 87%, the prediction accuracy of Yohan et al. (2018) method varies from 69% to 75%, and the prediction accuracy of the proposed method is always higher than 97%, which shows that the prediction result of this method is more accurate. The reason for the high prediction accuracy of the proposed method is that the method establishes the prediction index system through expert evaluation method, uses AHP to calculate the prediction index weight through hierarchical structure construction, judgment matrix construction, weight vector calculation, consistency test and calculation of combined weight vector, and uses fuzzy comprehensive evaluation method to build the mobile payment risk prediction model High precision prediction of mobile payment risk of communication operators.

2 Model consumption comparison:

In order to compare the comprehensive performance of different research methods more comprehensively, a comparison of predicting energy consumption is made, and the results are as follows.

Table 5 Comparing results of different research methods for predicting energy consumption

Project	*The proposed method*	*Method in Kang and Nyang (2017)*	*Method in Makki et al. (2016)*	*Method in Yohan et al. (2018)*
CPU share (%)	34.64	38.69	40.12	42.54
Memory utilisation (%)	12.36	12.54	18.69	20.84

It can be seen from Table 5 that the total CPU consumption is 38.69% and the memory utilisation rate is 12.54% by using the method of Kang and Nyang (2017) to build the system for payment risk prediction. Using the method of Makki et al. (2016) to build the system to predict the payment risk, the total CPU consumption is 40.12%, and the memory utilisation rate is 18.69%. Using the method of Yohan et al. (2018) to build a system for payment risk prediction, the total CPU consumption is 42.54%, and the memory utilisation rate is 20.84%. The total CPU consumption and memory utilisation rate are the highest of the four methods. Using the proposed method to build a system for payment risk prediction, the total CPU consumption is 34.64%, and the memory utilisation rate is 12.36%, which is far better than other methods. Therefore, this model is better than other methods in the computer system, the running consumption is less and the resource consumption is lower. The reason is that this method uses the fuzzy comprehensive evaluation method to build the mobile payment risk prediction model and realise the mobile payment risk prediction of communication operators. Because fuzzy mathematics can use less data to make an overall evaluation of things or objects restricted by many factors, it saves the consumption of resources.

5 Conclusions

In summary, with the development of science and technology and the wide application of electronic mobile terminals, mobile payment has become the main mode of payment, which brings great convenience for people to travel and consume, but at the same time, open network applications make mobile payment methods have great security risks. In view of this situation, this paper studies the risk prediction of mobile payment for telecom operators under the new business model, and designs a new risk prediction model for mobile payment in order to improve the mobile payment environment. The experimental results show that the prediction accuracy of the proposed method is always higher than 97%, and the prediction accuracy is better. The total CPU consumption is 34.64%, and the memory utilisation rate is 12.36%. The energy consumption is lower, which solves the problems of traditional prediction methods. Therefore, the method has the characteristics of high prediction accuracy and low memory utilisation. This method provides new ideas for the further development of mobile payment risk prediction technology for operators, and also provides an important reference for mobile payment risk aversion. It can greatly improve the security of mobile payment, enhance the trust of citizens in mobile payment, and provide security for the further development of mobile payment technology. In the future, we need to further develop the system by using the method of this paper, in order to realise the high unity of the research practice and theory.

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