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Research on Financial Risk Early Warning in the Online Game Industry Based on Random Forest and Fisher Discriminant Method

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Abstract: *With the rapid rise of the online game industry and the intensification of market competition, online game enterprises face different degrees of financial risks. It is necessary to establish an effective financial risk early warning model. Based on the online game industry, this paper constructs an index system from six dimensions, and makes an empirical study on financial risk early warning. First of all, a financial risk early warning model based on the random forest is constructed, and the prediction accuracy is as high as 100%, but the machine learning model has poor explanatory ability. Therefore, according to the index of random forest screening, a financial risk warning model based on the Fisher discriminant method is established. This model optimized the prediction effect of the original fisher's discriminant model and the prediction accuracy reached 87.5%. Finally, suggestions are made from the three aspects of cash flow, solvency and profitability of online game enterprises, and national support policies.*

Keywords: *Online game industry; Financial risk warning; Random Forest; Fisher's discrimination method*

1. Introduction

With the rapid development of domestic information technology, the continuous upgrading of the consumption structure, and the continuous transformation of social concepts, online games have been sought after by the social masses, especially young people, with their strong ornamental, participatory and social characteristics. The "14th Five-Year Plan" clearly states that China will vigorously layout strategic emerging industries such as the digital economy and future industries. In order to ensure that the online game industry can achieve rapid and healthy development, it is essential to analyze the financial risks of online game enterprises and respond reasonably. Guanyin [1] used the Bayesian discrimination method to study the financial risk early warning of the manufacturing industry. It concluded that the manufacturing industry should improve its crisis awareness and improve the financial crisis early warning mechanism. Zhang Xiaoyan [2] used the gray forecasting model to study the financial risk early warning of the real estate industry, and concluded that the real estate industry should adhere to a steady operation strategy and avoid overdevelopment. Reed Flute [3] Used factor analysis method and cluster analysis method to study the financial risk early warning of the agricultural industry. It concluded that the lack of profitability in the agricultural industry is the most important reason for inducing the financial crisis of enterprises, and this document provides a new idea for the subsequent research on financial risk early warning.

As an essential part of China's tertiary industry, the online game industry has played a prominent role in promoting economic development and made outstanding contributions to realizing economic transformation. Therefore, the study of this industry can not only provide a reference for the analysis of the financial risk of online game enterprises, but also play a vital reference significance for the long-term healthy development of China's tertiary industry economy. Compared with the relevant research literature at home and abroad, the marginal contributions that this paper may provide are: First, this paper uses machine learning methods to optimize statistical models, which make up for the shortcomings of machine learning models and statistical models, and improve the prediction accuracy of the model while ensuring that the model is interpretable. Second, the research related to financial risk early warning is mainly concentrated in the real estate industry, manufacturing industry, and pharmaceutical industry, and the online game industry research field is still blank. Therefore, combined with the current literature research results, this paper uses machine learning methods to optimize the statistical model to analyze online game

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enterprises' financial risks and expands the boundaries of the existing financial early warning research field.

2. Establishment of an indicator system for enterprise financial risk early warning model

2.1. Establishment of the indicator system

This paper aims to build a risk warning model for the financial health of online game enterprises. Combined with the existing literature [4,5,6] and the particularity of the online game industry, this article will establish an indicator system from six aspects: solvency, profitability, operational ability, development ability, enterprise value multiples, and cash flow. Solvency is an important factor in judging the financial position and operating results of enterprises, and the main indicators are quick ratio (X_1), equity multiplier (X_2), and cash flow interest protection multiple (X_3). Profitability is an important guarantee to ensure the survival and development of enterprises and improve the market competitiveness of enterprises. It is also the core link of an enterprise financial analysis. The main indicators are operating net profit margin (X_4), operating cost ratio (X_5), and return on total assets (X_6). The operational capacity reflects the efficiency and effect of the use of economic resources in the daily business activities of the enterprise, and the main indicators are total asset turnover rate (X_7), current asset turnover rate (X_8), and the accounts receivable turnover rate (X_9). Development capacity refers to the potential ability of the enterprise to maintain further expansion in the process of operation, and the main indicators are the growth rate of total assets (X_{10}), the growth rate of net assets per share (X_{11}), and the growth rate of shareholders' equity (X_{12}). The enterprise value multiple is a valuation indicator that reflects the market's expectations for the prospects of the enterprise, and the main indicators are price-to-earnings ratio (X_{13}), price-to-book ratio (X_{14}), and price-to-sales ratio (X_{15}). Cash flow is the key to the normal operation and development of the enterprise, and the main indicators are net cash content of operating income (X_{16}) and cash flow to debt ratio (X_{17}).

2.2. Sources of Data

The data in this article is mainly derived from the Oriental Wealth Choice financial terminal and the CSMAR Database. Through the screening and pre-processing of the data, twelve ST enterprises and twelve non-ST enterprises were randomly selected, for a total of twenty-four online game companies. Based on the above indicator system, the financial indicator data of the above enterprises in 2020 are empirically analyzed.

3. Construct a financial risk early warning model based on random forest

3.1. Research ideas

In order to build a risk warning model for the financial operation status of online game enterprises, this paper first uses a machine learning method to model the financial risk early warning model with higher prediction accuracy. Random forest is an integrated classification algorithm that combines the Bagging algorithm and the random subspace method, while using the decision tree as the base classifier. Because a random forest is a collection of multiple decision trees, the model is more robust, and the prediction accuracy is higher, avoiding overfitting. In addition, random forests can automatically output the importance ranking of variables in the data indicator set after fitting the data. In this paper, we propose to construct a financial risk early warning model based on random forest to study the signs of the financial crisis in online game enterprises.

3.2. Analysis of results

This article takes whether the listed enterprise is an "ST enterprise" as a sign of the financial risk crisis of the online game enterprise. If the enterprise belongs to an ST enterprise, the classification variable is Y=0. Otherwise, it is recorded as Y=1. In this paper, the original sample is randomly divided into two parts, 70% of the samples are selected as the training set for modeling, and the remaining 30% are tested as the testing set, and a total of 1000 decision trees are trained, and the prediction accuracy of the test set is as high as 100%. Although the financial risk warning model based on the random forest has high prediction accuracy, the black box attribute of the machine learning model leads to poor interpretability. Therefore, the output of the machine learning model cannot be adequately explained by

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financial indicators, that is, the financial risk early warning model based on the random forest is not ideal. Based on the established random forest model, the feature importance ranking of each indicator is generated, as shown in Figure 1. Among them, net cash content of operating income (X_{16}), cash flow to debt ratio (X_{17}), and cash flow interest protection multiple (X_3) are more significant.

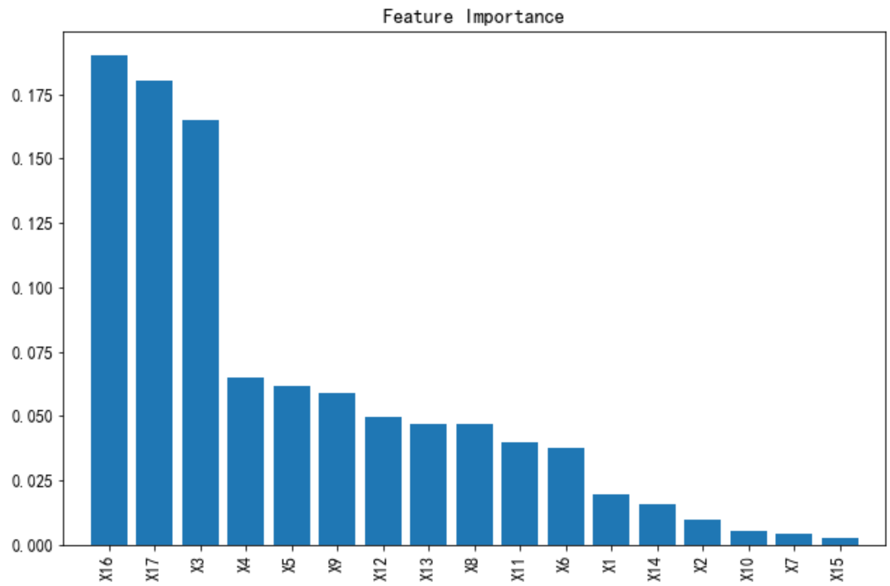

Figure 1: Descending order of feature importance of each indicator

4. Construct a financial risk early warning model based on Fisher's discriminant method

4.1. Research ideas

Although the random forest model's prediction effect is good, the model's interpretability is too poor, and the Fisher discriminant method complements it and has strong interpretability, but the model prediction effect is poor. Therefore, this paper will use the stochastic forest algorithm to optimize the statistical model to construct a financial risk early warning model based on Fisher's discriminant method. In this optimization model, the top five important features of the above random forest algorithm are selected, that is, net cash content of operating income (X_{16}), cash flow to debt ratio (X_{17}), cash flow interest protection multiple (X_3), operating net profit margin (X_4) and operating cost ratio (X_5) of online game enterprises' financial risk judgment score.

4.2. Analysis of results

4.2.1. Significance test of the model

This paper uses the Box's M test to test whether there is a significant difference in the covariance matrix of ST enterprise and non-ST enterprise data, as shown in table 1. It can be seen that the F-statistic result is 169.329, and the p-value is very close to 0, so this model is significant, illustrating significant differences between ST enterprises and non-ST enterprises.

Table 1: Homogeneous tests for covariance matrices

Box's M(B)	F test			
	Approx	d_{f1}	d_{f2}	P
169.329	8.465	15	1948.737	0.000

To test whether the selected financial metrics differ significantly from comparable enterprises, Wilks' Lambda was used to test this paper. As can be seen from Table 2, the indicators of net cash content of operating income (X_{16}) and cash flow to debt ratio (X_{17}) have significant differences at the significance level of 0.01. The indicators of operating cost ratio (X_5) have significant differences at the significance level of 0.1. The indicators of cash flow interest protection multiple (X_3) and operating net profit margin (X_4) have significant differences at the significance level of 0.2.

ISSN 2616-5902 Vol. 4, Issue 7: 93-98, DOI: 10.25236/AJBM.2022.040716

Table 2: Wilks' Lambda test

index	Wilks' Lambda	F test	d_{f1}	d_{f2}	P
X_{16}	0.570	16.579	1	22	0.001
X_{17}	0.530	19.520	1	22	0.000
X_3	0.916	2.025	1	22	0.169
X_4	0.912	2.118	1	22	0.160
X_5	0.880	2.992	1	22	0.098

To test the validity of the analysis function, Wilks' Lambda is used. It can be seen from Table 3 that the chi-square statistic result of the model is 15.231, and the p-value is 0.009. Hence, the model is significant at the significance level of 0.05, indicating that the discriminant analysis function established based on the above indicators is valid.

Table 3: Wilks' Lambda model significance test

Function testing	Wilks' Lambda	Chi-square	d_f	P
	0.458	15.231	5	0.009

4.2.2. Analysis of the results of the model

Fisher discriminant function is a linear discriminant function based on the analysis of variance and constructed according to the characteristics of each class. In this paper, based on the index data of 12 ST enterprises and 12 non-ST enterprises, using SPSS statistical software, the standardized Fisher discriminant function is solved as follows:

$$Y^* = 0.5588X_{16}^* + 0.6316X_{17}^* + 0.0751X_3^* + 0.0977X_4^* + 0.1223X_5^* \tag{1}$$

From the standardization code discriminant function (1), it can be concluded that after the normalization of the five index coefficients selected for this model, the coefficients are all positive, that is, there was a positive correlation between the target enterprise's discriminant score Y and the selected indicator X. Because the coefficients of cash flow to debt ratio (X_{17}) and net cash content of operating income (X_{16}) are larger, the cash flow of online game enterprises has a greater impact on their financial position. At the same time, solve the Fisher discriminant function as follows:

$$Y = 0.0242X_{16} + 2.4467X_{17} + 0.0022X_3 + 0.0001X_4 + 0.0006X_5 - 0.9039 \tag{2}$$

The output of the SPSS software shows that the centroid value of the ST enterprise group is -1.042, and the centroid value of the non-ST enterprise group is 1.042. In order to determine the category of the target enterprise, it is only necessary to substitute the five index values of the target enterprise into the functional formula (2), and then compare the resulting discriminant function value with the function value at the center of mass of each group. The function value is close to which group center of mass belongs to which category. In order to make the judgment results more accurately reflect the actual financial situation of the enterprise, the most authentic financial information is provided to the information users. In this paper, the distance between the two groups of centroids is equally divided, and the warning level of online game enterprises is divided into five levels. The classification results are shown in Table 4.

Table 4: Classification of the financial status of online game enterprises

Discrimination against the outcome	Financial position	Alert level
$Y \leq -1.042$	Extremely poor	I
$-1.042 < Y \leq -0.347$	Poor	II
$-0.347 < Y \leq 0.347$	Average	III
$0.347 < Y \leq 1.042$	Good	IV
$Y > 1.042$	Excellent	V

When the financial situation of the enterprise is extremely poor, it indicates that the risk of delisting faced by the enterprise is extremely high, and investors should avoid investing in such enterprises. When the financial situation of the enterprise is poor, it indicates that the enterprise has a financial crisis to a large extent, and the enterprise should pay attention to whether there are mistakes in its own financial decision-making and whether the capital chain is broken. When the financial situation of the enterprise is average, the enterprise should pay close attention to the organizational structure such as whether the established financial management system is reasonable and whether the financial relations of various departments are chaotic, and formulate relevant measures to strengthen financial control. When the

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financial situation of the enterprise is good, it indicates that the financial risk "prevention" mechanism adopted by the enterprise in the course of operation is running well, and it is enough to continue to maintain routine monitoring. When the financial situation of the enterprise is excellent, it indicates that the enterprise departments operate efficiently, and investors can invest in such businesses after comprehensive consideration.

4.2.3. Effect analysis of the model

Firstly, in this paper, an optimized model based on five financial indicators screened by the random forest algorithm as discriminant variables is tested, twenty-four sample companies are used as training data, and one enterprise is selected from the training sample for prediction. The classification results show that the overall prediction accuracy is 91.7% at 100% and 83.3%, respectively, but this also results in the prediction objects of the model only being suitable for twenty-four selected enterprises in this paper, which can not be applied to the entire online game industry. In order to broaden the scope of application of this model, this paper adopts the leave-one-out method for cross-verification. Each time, twenty-three companies were selected to train the data, leaving one as a test sample to assess the accuracy of the predicted results based on the average of the twenty-four sets of test results. In cross-validation, the prediction accuracy of ST enterprises and non-ST enterprises is 100% and 75% respectively, and the overall prediction accuracy is 87.5%. The prediction accuracy under cross-validation is more of reference significance for the entire online game industry.

In addition, this paper further examines the original model constructed with all financial indicators as discriminant variables. If all twenty-four sample companies are used as training data, ST and non-ST enterprises' prediction accuracy is 100%. If cross-validation is used, the prediction accuracy of ST enterprises and non-ST enterprises is 66.7% and 75%, and the overall prediction accuracy is 70.8%. It can be seen that the prediction accuracy of the optimization model under cross-validation is greatly improved compared with the prediction accuracy of the original model, indicating that the financial risk early warning model based on the Fisher discriminant method constructed in this paper has high credibility. According to the financial data provided by online game companies, relevant information users can use the model to determine the category of the target companies and further understand its financial status.

Table 5: Model classification results

Forecast group membership information	Optimized model				Original model			
	ST	0	1	total	ST	0	1	total
Original sample	0	12	0	12	0	12	0	12
	1	2	10	12	1	0	12	12
Cross-validation	0	12	0	12	0	8	4	12
	1	3	9	12	1	3	9	12

5. Conclusions and policy recommendations

This paper focuses on the financial risk warning of the online game industry. Combined with the existing literature and the particularity of the online game industry, this paper establishes an indicator system from six dimensions: solvency, profitability, operational ability, development ability, enterprise value multiples and cash flow. The financial data of twelve ST enterprises and twelve non-ST enterprises were selected, and the stochastic forest algorithm was used to model. A financial risk early warning model based on Fisher's discriminant method was constructed on this basis, with a prediction accuracy of 87.5%. The optimized model makes up for the drawbacks of the machine learning model and the statistical model, improves the model's prediction accuracy while ensuring that the model is interpretable, and provides a new idea for the subsequent research on financial risk early warning.

Through the empirical study of the financial risk warning of online game enterprises, this paper puts forward the following three suggestions: First, online games. The financial crisis of the enterprise is closely related to the cash flow of the enterprise itself, and the management should pay close attention to the management and application of the enterprise's cash flow, find the issues as soon as possible, and take remedial measures. Second, the enterprise should pay attention to its own solvency and profitability. Under the premise of the healthy operation of funds, the management should clarify the ownership of monetary and non-monetary assets. Control the overall debt level and profitability of the enterprise. Third, pay attention to the industrial support policies issued by the state and the government, combine the business objectives of enterprises, formulate strategic plans in line with the actual development of

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enterprises, and steadily advance in the market environment where opportunities and challenges coexist, so as to promote the sustained and healthy development of the tertiary industry economy in China.

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