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Internet Financial Risk Management Under the development of Deep Learning

Ziai Wu[1, 2], Qiao Zhou[3], Chengcheng Wu[1], Renwei Shu[4]

[1]Local Research Center of E-commerce Service, Chizhou University, Chizhou 247000, China
[2]Philippine Christian University Center for International Education, Manila, 1004, Philippines.
[3]Chizhou Emerging Industries Investment Group, Chizhou 247000, China
[4]Chizhou Tobacco Company of Anhui Province, Chizhou 247000, China
Email: 83448520@qq. com, 2418513240@qq. com, 1101656995@qq. com, 1084489965@qq. com

Abstract: With the rapid development of Internet finance in both quantity and scale, various challenges have emerged. Deep learning is a promising tool to explore the optimal algorithm to analyze input variables that affect Internet financial risks, and corresponding classification to manage and minimize those risks. This study employs a questionnaire and data analysis to evaluate Internet financial risks, with a focus on psychological risk, social risk, technical risk, moral risk, and material risk. The research provides theoretical and practical value in the field of Internet financial risk management. The results of the study demonstrate that psychological risk, social risk, technical risk, material risk, and moral risk are all significant factors that contribute to Internet financial risks. Additionally, higher education is found to be a protective factor against Internet financial risks, while higher income is associated with greater risk. Furthermore, psychological risks were found to have the most significant impact on Internet financial risks.

Keywords: Deep learning, Internet finance, Risk, Big data, Risk management system

1. Introduction

The wide application of Internet technology brings convenience to the work and life of Internet finance users, and gives birth to the innovation of online credit and Internet finance. As a financial model based on Internet technology, online credit is developing rapidly because of its lower operating costs, wider word-of-mouth spread and faster financial returns compared with traditional financial loans. With the development of the number and scale of Internet finance, it also faces many problems. Domestic Internet finance enterprises are generally faced with many problems, such as difficulties in risk control. Typical risk control problems of Internet finance are mainly reflected in the following aspects: first, the risks of Internet finance are hidden;Second, Internet financial risks spread fast and spread widely;Third, it is difficult to regulate Internet financial risks, especially in terms of regional management.

At present, there are abundant research results on the combination of deep learning and Internet finance risk control. Deep learning can find the optimal algorithm to explain the input variables affecting Internet finance risk and corresponding classification, select the method suitable for Internet finance risk management and obtain the best results. Therefore, this study combines the background of deep learning to carry out research on Internet financial risk management, which has important theoretical and practical research value. This study firstly carries out theoretical support and literature review research, and then introduces the differences between Internet finance and traditional financial risks in detail. Finally, through questionnaire survey and data analysis, the survey results and analysis conclusions of Internet finance risk management are drawn.

2. Relevant theoretical support and literature review

2. 1 Connotation of Internet financial risks

Internet finance refers to a new model in which traditional finance is combined with the emerging Internet and Internet technology is used to realize financial financing services[1]. Technology is the support of Internet finance, which uses big data, cloud computing, deep learning and other technologies to provide support. However, Internet finance is still a fund financing service in essence, which realizes the value exchange of funds across time and space. After the combination of financial financing and Internet technology, the Internet itself has potential risks such as information network security risks, platform operation security risks, terminal operation security risks, user privacy leakage and so on. Internet finance will also face such potential risks. Moreover, the trans-regional, trans-boundary and trans-temporal

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characteristics of Internet finance and the complexity of mixed operation of Internet finance also make it possible to cause systemic risks.

Different from traditional financial risks, the risks of Internet finance are related to the characteristics of Internet across time and space and the rapid development of Internet technology, which are mainly reflected in the following three aspects: First, Internet finance significantly reduces costs, improves efficiency and increases convenience. Second, Internet finance does not have manual due diligence, face-to-face signing, mortgage, notarization and other face-to-face links. Third, the number of loan orders of Internet finance users is large, the amount of a single loan order is low, the phenomenon of long loans is common, and the composition of the loan customer group is complex and unstable. Therefore, with the continuous accumulation of historical borrowing data of Internet financial users, Internet financial enterprises begin to apply big data technology and deep learning algorithm in credit risk identification, prediction and control.

2. 2 Causes and characteristics of Internet finance risks

Internet finance is the product of the development of Internet technology, social and economic development and financial innovation that keeps pace with The Times of traditional finance. The participants of Internet finance include Internet enterprises, investors, lenders, borrowers, third-party payment institutions, third-party guarantee structures, banks, consumer finance companies, small loan companies, etc. , which is an interactive financing activity formed among these participants. And the communication characteristics of the Internet can magnify the scope and ways of improper financial financing behaviors, which brings great risks to social stability and economic development.

The causes of Internet financial risks are the causes and conditions that lead to the occurrence of financial accidents or financial losses. They are composed of three basic elements: risk factors, risk accidents and losses. Risk has objective possibility, measurability and contingency, which can be measured with probability, reflected in the degree of difference between the expected financial results and the actual results. Therefore, the expected value of Internet financial risk is the product of the probability of risk occurrence and the loss.

Generally, according to the nature and causes of risks, Internet financial risks can be divided into five types: substantial risk, moral risk, psychological risk, technical risk and social risk.

1. Substantial risk

Material risk is the objective condition that guides the occurrence of an accident or loss. For example, interbank savings, the establishment of a capital pool, the absorption of public funds.

2. Moral hazard

Moral hazard is when an accident or loss occurs as a result of an intentional act or omission. For example, evasion of debts, running away with money, issuing false bids and self-financing, etc.

3. Psychological risk

Psychological risk is the subjective negligence or negligence of people that causes an accident or loss to occur. For example, lax examination and approval of loans, credit default, non-standard operation.

4. Technical risks

Technical risk refers to the imperfect information technology that leads to accidents or losses. For example, DDOS traffic attacks, security breaches.

5. Social risks

Social risk refers to the legal system and cultural environment that may lead to an accident or loss. For example, public opinion leads to rigid payments, lack of financial regulation, and low barriers to entry.

Internet finance has substantial, moral, psychological, technological and social risks, but as an important area of financial innovation and development, it plays an important role in developing the small, dispersed and long-tail market of inclusive finance through its technical characteristics and means. The risks of Internet finance have the following characteristics:

1. Asymmetry. Asymmetry manifests itself in asymmetric information. In the financial market, information asymmetry is a common phenomenon. In the Internet environment, information asymmetry still exists, which is related to the different channels of information transmission, the different abilities of individuals to process information, and the information asymmetry among various participants of Internet finance.

2. Openness. Openness is embodied in the fact that anyone can access and conduct financing related activities through the Internet, regardless of the traditional time and space constraints. Openness makes Internet finance more accessible and has a wider geographical scope, which directly determines that risks can be spread from a terminal to the whole network, and from a single individual to the whole group, leading to changes in the order of Internet finance.

3. Wide coverage. Customers of Internet finance can break through the constraints of space and time, search for financial resources directly through the network, and obtain financial services directly, so the customer base is wide and the coverage is wide. Relying on the network, Internet finance can cover villages and towns that cannot be covered by traditional finance.

4. High penetration rate. Internet finance has changed people's financial consumption behavior, improved people's cognition and acceptance of financial consumption behavior, and the online, app-based and mini program-based business of traditional financial institutions such as banks has further promoted the penetration rate of Internet finance to people. According to the iResearch report, the online penetration rate of China's consumer credit has increased from 0. 4% in 2014 to 69. 4% in 2021.

2. 3 Prediction methods of Internet financial risks

By reviewing and summarizing the literature on Internet finance risks and deep learning algorithms, it is concluded that there have been some achievements in the current research on Internet finance risk control by deep learning algorithms, focusing on building machine learning models or improving machine learning models. At present, there are two mainstream methods in the academic world: the prediction method based on statistics and the prediction method based on deep learning.

The Internet financial risk prediction methods based on statistics mainly include logistic regression method, expert discriminant method, discriminant analysis method and so on. The default risk prediction method based on statistics can be divided into accounting model and market model according to the different data types in the field of practice and application. Depending on the financial statements of enterprises, accounting model applies different statistical methods to carry out the assessment of default risk. The accounting model is widely used, including Altman (1968) Z-score model and Ohlson (1980) Logistic model. Market models rely on stock, futures, bonds and other market data information, derive and calculate the theoretical model, calculate the default probability of financial enterprises, market models are widely used mainly Merton model and KMV model.

Internet financial risk prediction method based on deep learning: Deep learning is derived from the development of artificial neural network and contains complex and multi-level learning structure. The establishment of deep learning is to imitate the learning mechanism of human brain. By learning each data feature, the deep learning model inputs new features into the next layer. In this process, the new features are obtained through the specific feature transformation of the learned data features, which improves the prediction effect of the model. When applying the deep learning model, its algorithms mainly include Restricted Boltzmann Machine (RBM), Markov chain Monte Carlo (Markov chain Monte Carlo, MCMC), Gibbs sampling, Reconstruction error, annealing importance sampling (AIS), etc.

Risks in the financial sector, mainly default risk and credit risk. Domestic and foreign scholars have carried out risk assessment in the financial field through various models, including Orgler Y E (1970) linear regression method, Li Shuguang (2003), Hsieh N-C (2005), Gao Guping, Liu Shuan (2007), Liu LAN (2011) and other neural network credit scoring models. It has become an important standard to measure the quality of Internet financial services to identify and forecast Internet financial risks more accurately and more quickly by using big data and deep learning algorithms. Risk identification and prediction of Internet finance are the basis for Internet finance enterprises to survive in the rapid development of Internet finance. The methods related to Internet financial risks are as follows:

Linear evaluation of default risk is used to improve the accuracy of default risk prediction.Orgler Y E (1970) earlier applied the method of linear regression to the assessment of default risk. Linear regression requires correlation between independent variables and dependent variables, which requires in-depth processing to predict and classify default risk[2].

Use neural network model to evaluate credit risk, improve the speed and accuracy of credit risk identification and prediction.Li Shuguang (2003) used the neural network model in consumer credit assessment[3]. Hsieh N-C (2005) proposed a data mining algorithm based on neural network and cluster integration, which was applied to the construction of credit scoring model through deep network. In the process of classification of sample data set by clustering method, sample data is preprocessed according to K-meads clustering, and after eliminating unrepresentative sample data, credit score is performed[4]. Gao Guoping and Liu Shuan (2007) analyzed the credit risk and credit score of Chinese enterprises, built the credit score measurement model of radial basis function neural network, used the data for discrimination and analysis, and improved the learning algorithm of radial basis function neural network. Radial basis function neural network has the research and promotion value for scoring system[5]. Liu LAN, Wang Xia, Lin Hongxu and Gao Jianshi (2011) modeled credit risk control based on BP neural network, optimized the BP neural network algorithm to find the optimal parameters, and carried out experiments relying on the credit data set. The results showed that the hybrid BP neural network algorithm could significantly improve the prediction effect of high-risk users[6]. Gang Wang (2011) used Boosting to improve the accuracy of model according to logistic regression, decision tree, artificial neural network and support vector machine as base classifiers[7]. Jingrui (2012) combined and compared the logistic regression and neural network models, and the analysis results showed that the combination of the two models had better credit evaluation effect than the single model[8]. Budak H and Erpolat S (2012) carried out credit analysis and prediction analysis on four models including logistic regression model, MARS, support vector machine and neural network, and the experimental results showed that the four models had significant effects and had practical application value in credit risk prediction[9]. Jochen Kruppa, Alexandra Schwarz and Gerhard Arminger et al. (2013) respectively used random forest, k-nearest neighbor classification algorithm and Bagged-K nearest neighbor algorithm to evaluate consumer risks. The evaluation results show that the effect of random forest is better than that of K-nearest neighbor classification algorithm and Bagged-K nearest neighbor algorithm[10]. Hussain Ali Bekhet and Shorouq Fathi Kamel Eletter (2014) constructed and compared two risk assessment models, logistic regression function and radial basis function. The comparative analysis results show that the radial basis risk assessment model is more effective in predicting and evaluating potential credit default risks[11]. Fang Quannan, Zhang Guijun and Zhang Huiying (2014) constructed the Lasso-logistic model for personal information risk and determined the key factors of credit risk to achieve better prediction effect[12]. Paulius Danenas and Gintautas Garsva (2015) used the Support Vector Machine (SVM) model to evaluate the risk of loan default. And compared this model with the Logistic Regression and Radial basis function network (RBF network) models, the comparative analysis showed that SVM model had the best evaluation effect, followed by radial basis function network model[13]. Liu Kaiyuan (2016) combined random forest and logistic regression and made a comprehensive comparison around RFL model, KNN, decision tree algorithm and BP neural network algorithm. The results showed that RFL model was superior to KNN, decision tree algorithm and BP neural network algorithm[14]. Yu Xiaohong and Lou Wengao (2016) used random forest to conduct algorithm training on 87 samples, with an accuracy of 100%, and carried out risk assessment, early warning and empirical research on P2P online lending[15]. Somayeh Moradi and Farimah Mokhatab Rafiei (2019) constructed a new model combining fuzzy calculation and fuzzy recognition to train and predict the data of Iranian banks (2008-2016), and the results showed that the new model had significant effects[16].

In summary, through the literature review and summary of Internet finance risk and deep learning algorithm, it is believed that the current research on the risk control of Internet finance by deep learning algorithm, the contribution of the prediction method of deep learning is mainly divided into two aspects: First, deep learning has powerful data mining learning ability, which can more accurately excavate the laws hidden in the deep data, and is more suitable for the prediction and risk identification of the Internet financial market. Meanwhile, the application of deep learning also continuously optimizes the algorithms applicable to the deep network, and promotes the progress of the empirical application research methods of Internet finance. Second, the application of deep learning algorithms in the field of Internet financial risk management, and the research results have also promoted the development and improvement of related Internet financial institutions, Internet financial industry and Internet financial regulation.

3. Questionnaire survey and data analysis

3. 1 Questionnaire design process

According to the research purpose, the research object should be determined, the online questionnaire design should be completed, and the questionnaire should be shared and distributed through wechat, QQ and other means. 259 valid questionnaires were collected. The collection of questionnaires is shown in Table 1.

Table 1 Results of questionnaire collection

Source channels	Quantity	Percentage
wechat	234	90. 35%
Mobile submission	24	9. 27%
Links	1	0. 39%

3. 2 Calculation method of questionnaire survey

The questionnaire results were analyzed by SPSS for reliability and validity. Table 2 shows that the reliability coefficient value is 0. 875, greater than 0. 8, indicating high reliability quality of the research data. As for the "α coefficient of deleted items", the reliability coefficient does not increase significantly after any item is deleted, which indicates that the item design is reasonable and the item should not be deleted. KMO and Bartlett tests were used to verify the validity. Table 3 shows that KMO value is 0. 876, larger than 0. 8, indicating that it is very suitable for information extraction.

Table 2 Cronbach reliability analysis of questionnaire

Number of items	Sample size	Cronbach α coefficient
24	259	0. 880

Table 3 KMO and Bartlett tests

KMO values		0. 876
Bartlett test for sphericity	Approximate chi-square	3214. 588
	df	276. 000
	p value	0. 000

3. 3 Contents of the questionnaire

The questionnaire consists of two parts: basic information and questionnaire information. The basic information consists of four parts: gender, age, income and education level (see Figure 1, 2, 3 and 4). Questionnaire information is designed around Internet financial services, Internet financial products, Internet financial accidents, Internet financial risk causes, Internet financial development trend, etc.

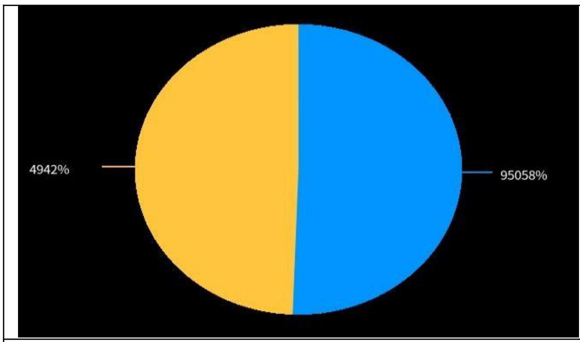

Figure 1 Gender distribution of respondents

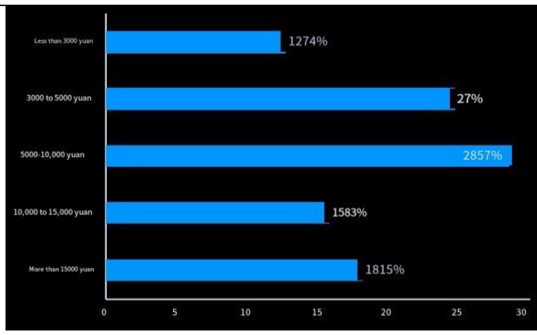

Figure 2 Monthly income of respondents

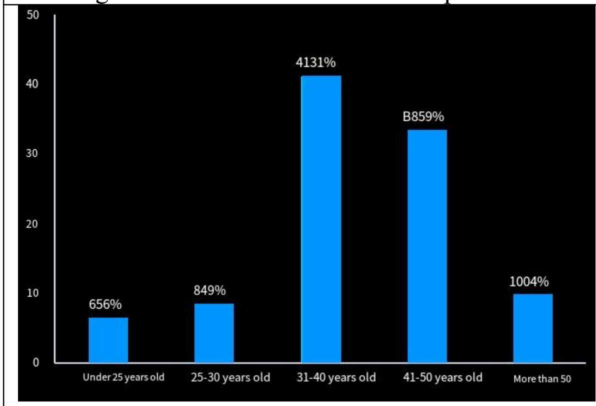

Figure 3 Age distribution of respondents

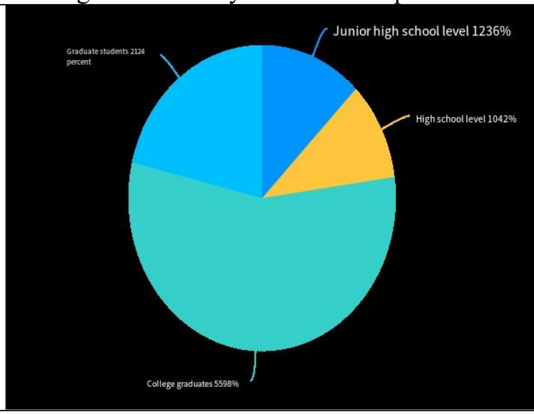

Figure 4 Education status of respondents

4. Analysis and discussion

4. 1 Internet finance risk income model evaluation

The structural equation model (SEM) was used to quantify the influence structure relationship and measurement relationship of psychological risk, social risk, technical risk, moral risk and material risk. Financial experts and senior personnel in the financial industry conducted risk assessment on each level of indicators, and evaluated the monthly income and Internet financial risk model, which were successively psychological risk (0. 918), social risk (0. 854), technical risk (0. 850), moral risk (0. 757) and material risk (0. 752). The results of income assessment are shown in Table 4 and Figure 5.

Table 4 Summary of evaluation models

X	→	Y	Non-standardized regression coefficient	*SE*	*z (CR value)*	*p*	Standardized regression coefficient
Monthly income	→	Risk	0. 241	0. 132	1. 823	0. 068	0. 202
Monthly income	→	3. Your monthly income	1. 000	-	-	-	0. 569
Risk	→	Social risk refers to the legal system and cultural environment that may cause an accident or loss to occur. For example, public opinion leads to rigid payments, lack of financial regulation, and low barriers to entry.	0. 919	0. 084	10. 941	0. 000	0. 854
Risk	→	Technical risk refers to the information technology is not perfect, resulting in accidents or losses. For example, DDOS traffic attacks, security breaches.	1. 088	0. 088	12. 321	0. 000	0. 850
Risk	→	Psychological risk is people's subjective negligence or negligence that causes accidents or losses to occur. For example, lax examination and approval of loans, credit default, non-standard operation.	1. 082	0. 081	13. 343	0. 000	0. 918
Risk	→	Moral hazard refers to intentional actions or omissions that result in an accident or loss. For example, evasion of debts, running away with money, issuing false bids and self-financing, etc.	0. 893	0. 090	9. 947	0. 000	0. 757
Risk	→	Material risk is the objective condition that guides the occurrence of an accident or loss. For example, interbank savings, the establishment of a capital pool, the absorption of public funds.	1. 000	-	-	-	0. 752

Note: → Indicates regression influence relationship or measurement relationship

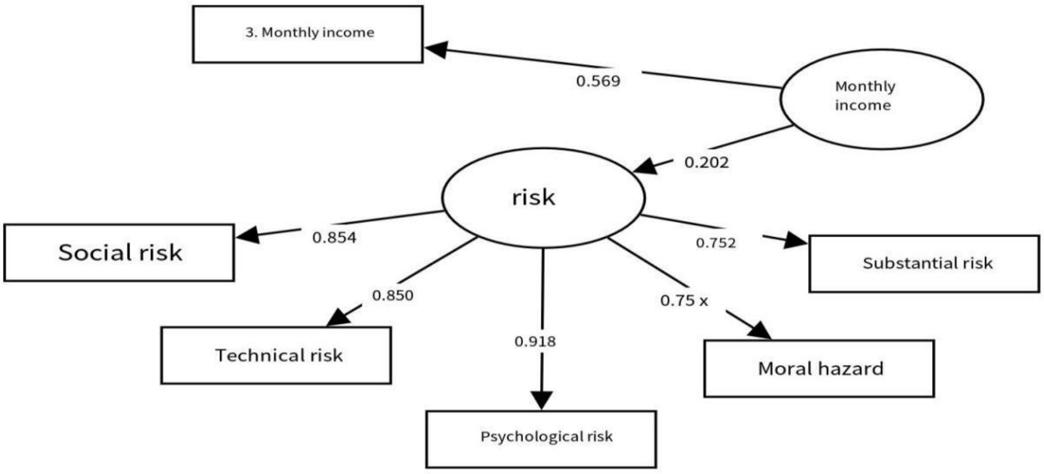

Figure 5 Income and Internet finance risk assessment

4. 2 Evaluation of Internet finance risk education model

The structural equation model (SEM) was used to quantify the influence structure relationship and measurement relationship of psychological risk, social risk, technical risk, moral risk and material risk. Financial experts and senior personnel in the financial industry conducted risk assessment on each level of indicators, and assessed the education situation and Internet financial risk model, which were successively psychological risk (0. 921), social risk (0. 853), technical risk (0. 851), material risk (0. 753) and moral risk (0. 752). The evaluation results of education status are shown in Table 5 and Figure 6.

Table 5 Summary of evaluation models

X	-	Y	Non-standardized regression coefficient	*SE*	*z* (CR value)	*p*	Standardized regression coefficient
Education	-	Risk	0. 241	0. 117	1. 623	0. 058	0. 019
Education	-	4. Your education	1. 000	-	-	-	0. 538
Risk	-	Social risk refers to the legal system and cultural environment that may cause an accident or loss to occur.For example, public opinion leads to rigid payments, lack of financial regulation, and low barriers to entry.	0. 918	0. 084	10. 887	0. 000	0. 851
Risk	-	Technical risk refers to the information technology is not perfect, resulting in accidents or losses.For example, DDOS traffic attacks, security breaches.	1. 091	0. 088	12. 336	0. 000	0. 853
Risk	-	Psychological risk is people's subjective negligence or negligence that causes accidents or losses to occur.For example, lax examination and approval of loans, credit default, non-standard operation.	1. 085	0. 081	13. 347	0. 000	0. 921
Risk	-	Moral hazard refers to intentional actions or omissions that result in an accident or loss.For example, evasion of debts, running away with money, issuing false bids and self-financing, etc.	0. 891	0. 090	9. 889	0. 000	0. 752
Risk	-	Material risk is the objective condition that guides the occurrence of an accident or loss.For example, interbank savings, the establishment of a capital pool, the absorption of public funds.	1. 000	-	-	-	0. 753

Note: → Indicates regression influence relationship or measurement relationship

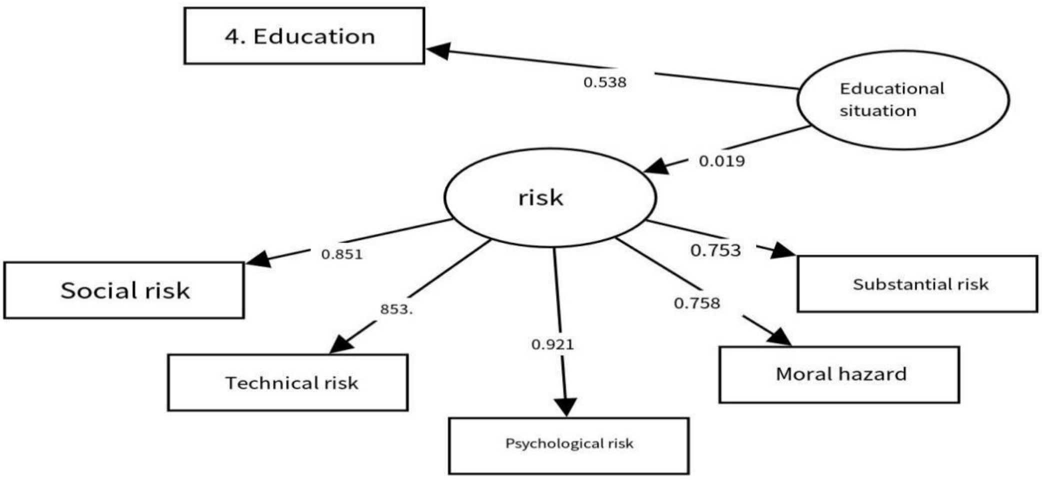

Figure 6 Education and Internet finance risk assessment

Figure 5 and Figure 6 show that in the eyes of financial experts and senior people in the financial industry, Internet financial risk is affected by psychological risk, social risk, technical risk, material risk and moral risk. Higher education can better resist Internet financial risks, higher income is more likely to lead to Internet financial risks, and psychological risk has the greatest impact on Internet financial risks.

5. Results and Discussion

In China, where the Internet is highly developed and the number of Internet users is as high as 1.051 billion, all kinds of financial information is expanding or even exploding, and people's ability to acquire information, identify risks, analyze problems and deal with risks has not been enhanced, on the contrary, it is weakening. Due to the psychological effect, people firmly believe the interpretation of authority figures. When facing the Internet financial information, people will only absorb the most favorable information for themselves and filter out the unfavorable information, so as to satisfy people's conformity, fluke and speculation psychology.

In order to strengthen the risk management level of financial enterprises and improve the accuracy of financial risk prediction, this paper analyzed the difference between Internet financial risks and traditional financial risks based on the deep learning algorithm, expounded the causes and characteristics of Internet financial risks, used the relevant theories and knowledge of deep learning, carried out questionnaire and data analysis, and drawn the research conclusions.The results show that psychological risk has the greatest impact on Internet financial risk, followed by social risk, technical risk, material risk and moral risk. The problem of Internet financial risk is not only the risk itself, but also the result of human nature and human psychology. Where there is investment, there is risk. Various financial risk cases fully show people's continuous pursuit of high returns and pursuit of hot investment spots. The pursuit of high returns and hot investment spots leads people to turn a blind eye to the risks of Internet finance. The psychological effects are generally reflected in the following aspects: First, the high returns of Internet finance are generally given priority; Second, ignore the objective existence of Internet financial risks; Third, they always think that Internet financial risks are far away from them. Fourth, when Internet financial risks come, there is nothing to do. Risk management of Internet finance is the cornerstone of all financial activities. It is of great significance to evaluate and identify risks.

There are psychological risks, social risks, technical risks, material risks and moral risks in Internet financial risks. Each risk has its own characteristics and objective laws, which need to be explored, analyzed, evaluated and identified by deep learning algorithms. The management of Internet financial risks requires knowledge of financial systematics, while the warning and prediction of risks require professional knowledge of big data and deep learning. The risk management of Internet finance can be comprehensively judged by big data technology, and the potential behaviors of users can be mined from massive and barren data to improve the accuracy of risk assessment of Internet finance. For risk management of Internet finance, deep learning algorithms can be used to build an early warning system for Internet finance risks, so as to improve the rapidity of risk identification and prediction. Therefore, this study combines deep learning background to carry out research on Internet financial risk management, which has important significance and research value of The Times.

The research on Internet Financial Risk Management Under the development of Deep Learning, through questionnaire and data analysis, proves that it has high potential and practical evaluation value to grasp the influencing factors of Internet financial risk. It can provide support for Internet finance risk decision makers, policy makers, research recipients and future researchers. At the same time, deep learning technology is used to carry out Internet financial risk management, reducing the difficulty of risk control strategy allocation. The future research direction will focus on deep learning algorithm, design and implement a set of online risk model test system of Internet finance, including system management module, user management module, product management module, risk monitoring module, risk early warning module, etc., and then analyze the test results of various scenarios, establish the risk control model of Internet finance, to meet the actual needs of financial enterprises.

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