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The Risk Analysis of Digital Inclusive Financial Platform Using Deep Learning Approach

WEI SHI[1,3], SI-QI LONG[1,3] AND YUE LI[2,3,+]
[1]*Guangxi Banking School*
Nanning, 530007 P.R. China
[2]*School of Business and Economics*
Universiti Putra Malaysia
Selangor, 43400 Malaysia
[3]*Guangxi Financial Vocational College*
Nanning, 530007 P.R. China

This paper intends to investigate the risk management of inclusive digital financial platforms. First, it explains the idea of smart cities, their function, and inclusive financial risk control technologies based on big data. The varieties of digital inclusive financial platforms and their risk profiles are next examined. The Back Propagation (BP) neural network is used to build a BP-KMV model based on the KMV model. Finally, utilizing M Company as a case study, this paper uses the BP-KMV model to examine the credit risk and risk management of unlisted enterprises on the digital inclusive financial platform. The results show that of the four unlisted companies, L Company has the greatest default rate (7.35%), while J Company has the lowest default rate (4.82%). The highest research and development (R&D) spending rate is 14.1% for J company, while the highest patent ownership rate is 43.09% for L company. The data demonstrates a negative correlation between the percentage of R&D expenditures and the default rate of unlisted enterprises. In other words, a larger default risk is associated with lower R&D expense rates. Additionally, there is a correlation between patent ownership and default rates that is positive, suggesting that higher patent ownership rates are linked to higher default rates. Additionally, the risk management technologies of M business can complement one another. The theoretical research of comprehensive digital inclusive finance risk control can be enriched by the risk analysis of digital inclusive financial platforms utilizing the BP-KMV model in the context of smart cities.

Keywords: smart city, BP neural network, digital inclusive finance, financial risk control, KMV model

1. INTRODUCTION

Digital inclusive finance uses digital technology to empower inclusive finance, solve the problems of high financing cost and limited-service coverage in traditional finance, and better promote financial services to the general public [1]. Smart city is a model of integrating a new generation of information technology into real life and an advanced form of urban informatization. According to the planning and pilot of relevant departments, more than 700 cities in China are planning and building smart cities [2]. The development of this smart city provides broad application scenarios and development opportunities for digital inclusive finance.

However, in the context of smart cities, the digital inclusive finance platform is facing a series of risk challenges. Firstly, because digital inclusive finance combines the charac-

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[+] Corresponding author: nolee36@gmail.com

teristics of Internet and inclusive finance, it may face higher financial risks compared with traditional finance, such as information security risks and credit risks. Secondly, the development of digital inclusive finance may be affected by regulatory policies, such as inadequate supervision or late rectification measures may adversely affect the operation of the platform. Especially in the field of online lending, the strengthening of regulatory policies has led many online lending companies to withdraw from the market, which has had a certain negative impact on peer-to-peer lending [3]. When new digital technology enters the inclusive finance market, if financial institutions lack strong risk control ability and effective risk management system, it may lead to the aggravation of financial risks and the recurrence of potential tragedies. Therefore, it is of great theoretical and practical significance to study how to effectively analyze and control the risks of digital inclusive finance platform under the background of smart cities.

In conclusion, this paper takes M company as an example based on the smart city's risk control technology. The default prediction KMV model is then integrated with deep neural network (DNN), and the credit risk of digital inclusive financing in M company is studied. This paper can serve as a benchmark for risk management practices at other financial technology firms or financial intermediaries. Additionally, it provides significant insights that might determine the future course of financial risk control. This paper intends to update risk warning signs, apply multiple technologies, and judiciously use leverage techniques to constantly improve the risk control capabilities of digital inclusive financial platforms. The risks associated with DNN-based digital inclusive financial systems are examined in Section 2. In Section 3, M company is used as an analytical case, and the market value and volatility of M company are solved using a trained BP neural network. The complete research project is summarized in Section 4 along with potential directions for more study.

2. RELATED WORK

The existing scholars' research on financial risks mainly focuses on the following aspects. On the financial risk early warning, Zhu and Liu [4] elaborated the research status and significance of financial risk early warning, the development background, status quo, and future challenges of K-means clustering algorithm. They also put forward a financial risk indicator system based on K-means clustering algorithm, selected indicators and processed data, built a financial risk early warning model based on K-means clustering algorithm, classified financial risk types, and optimized financial risk control [4]. In the aspect of financial risk of the Internet of Things (IoT), Zhu *et al.* [5] analyzed internal and external risk factors from different sources, and discussed the Z-score model of financial risk assessment of intelligent enterprises based on the IoT, and found that the main risk sources faced by the Internet of Things enterprises were external legal risk, industry competition risk (mainly affected by external environment) and external tenant credit risk (mainly based on their own characteristics) [5]. In terms of investors' risk perception, Landi *et al.* [6] investigated the impact of corporate social and environmental assessment on investors' risk perception, discussed the potential market risks of listed companies adopting sustainable and responsible corporate strategies, and tested the impact of corporate social performance on corporate financial risks by using double risk measurement standards, and found that investors were more uncertain about corporate sustainable development performance [6].

In addition, some scholars have analyzed financial analysis in other fields. In *et al.* [7] assessed the climate-related financial risks faced by energy infrastructure investment, and made asset-based and forward-looking risk assessments on three downstream energy assets, including natural gas, coal and solar photovoltaic power plants. They found that renewable energy investment might be more resilient to climate change than energy assets based on fossil fuels [7]. Liu *et al.* [8] used forward-backward stochastic differential equations to study the common options pricing problems in financial risk management. The results showed that fully discrete and decoupled forward-backward stochastic differential equations could effectively price spread options and optimal options [8]. Alrawad *et al.* [9] used two criteria (probability and consequence) and six different types of risks as decision-making alternatives to construct a three-tier decision-making model, collected data from managers/owners of small and medium-sized enterprises through questionnaires, and analyzed them according to the analytic hierarchy process. The results showed that the priority weight of risk criteria was 52% probability and 48% consequence. In addition, the risk of increasing bank fees ranked as the highest risk type faced by SMEs with an average weight of 18.8% [9].

The above research analyzes financial risks from different angles, but there are few studies on comprehensive risk control of digital inclusive finance. Meanwhile, most of the risk control cases of digital inclusive finance in society are not public, and the risk control system of M company has been in place for a long time. Therefore, this paper takes M company as a case-oriented and explores comprehensive risk control of digital inclusive finance.

3. RISK ANALYSIS OF DIGITAL INCLUSIVE FINANCIAL PLATFORM BASED ON DEEP NEURAL NETWORK

3.1 Big Data Risk Control Technology Based on Smart Cities

There is still no agreement on the precise concept of “smart cities”. Nevertheless, the integration of cutting-edge technologies and efficient public administration are at the heart of the enlarged definition of a smart city. The main emphasis is on improving urban infrastructure’s overall performance and maximizing public services [10]. Many academics have thoroughly and in-depth examined smart cities from a variety of angles. Some academics contend that smart cities have developed a conceptual pedigree of “technology – knowledge – governance integrity – composition” based on the global trend toward smart cities [11]. According to some academics, information technology forms the cornerstone of smart cities and has a distinct focus on “three governance”. Smart city institutions provide a link between technology and value [12]. In short, “smart cities” refer to the use of various information technologies or cutting-edge ideas to connect and integrate urban processes and services. This aims to increase the effectiveness of resource usage, improve urban management and services, and enhance the quality of life for inhabitants [13]. It may effectively integrate urbanization, industrialization, and information technology while reducing the “big city disease”. Additionally, it can boost the effectiveness of urban management, produce refined and dynamic management, and enhance the quality of life for inhabitants.

Inclusive finance has slowly made its way into the public with the development of smart cities. Small, short-term loans, frequent loans, and urgent demands are some of the distinctive characteristics of inclusive financing that lead to high servicing costs, low returns, and significant risks. Digital technology can help the inclusive finance sector operate sustainably by lowering service costs and enhancing risk control skills [14, 15]. The development of blockchain, cloud computing, and other technologies has made big data analysis for creating models from huge data. For digitally inclusive financial platforms, big data can give a significant volume of online data. Different dimensions can be established to evaluate the information status of borrowers through the examination of vast amounts of data.

Deep learning (DL), a machine learning technique based on multi-layer neural networks, entails stacking hidden layers between the neural network's input and output layers. DNN, deep convolutional neural network (DCNN), and recurrent neural network (RNN) are some of the often-employed DL processes [16]. With the aid of huge amounts of data and commercial objectives, DL integrates supervised and unsupervised learning's frameworks for neural network deployment, enabling target training with derived variable characteristics. When there are many different dimensions, a lot of data, and sparsity, DL is more important [17-19]. Consumer behavior and credit risk is found to be closely related in the study of credit risk analysis for online finance users based on DL, suggesting that DL has a certain reference value in credit granting. Digital assets become more trustworthy and reliable thanks to the decentralized, tamper-proof, traceable, asymmetric encryption, and smart contract aspects of block-chain, which can be extensively applied in the sphere of data sharing [20]. Notably, the characteristics of blockchain hold important benefits in developing a decentralized and unchangeable credit reporting sector. Better asset allocation is made possible by using blockchain for digital asset transactions.

3.2 Risk Analysis of Digital Inclusive Financial Platform

Digital inclusive finance is networked and financial, and it is distinguished by its complexity, infectiousness, and virtuality [21-23]. It makes use of Internet technology, which is sophisticated in and of itself. In terms of the financial business itself, there are various operating modes, and each mode has a different set of hazards. As a result, the risk associated with digital inclusive finance is quite complex. Digital inclusive finance operates across industries and borders, unlike most traditional financial institutions, which are independent. As a result, it is subject to regulation from several regulatory bodies. A broad network for capital transmission is created by the intertwining of multiple capital chains and institutions. Any data transmission flaw in a link in this chain can spread quickly over the Internet, increasing market risks in a variety of industries. Therefore, the danger connected to inclusive digital finance is quite contagious. Digital inclusive finance, which is based on this technology, also inherits a virtual character due to the Internet's virtual nature. It represents and digitalizes actual life and creates more opportune and covert conditions for a variety of illegal acts.

The primary purpose of digital inclusive finance, which is an extension of traditional inclusive finance, is to support the actual economy [24]. The risk decomposition structure theory states that various risk components each contribute to the occurrence of a risk. As shown in Fig. 1, digital inclusive finance involves risks because of the use of digital technology in addition to common financial risks similar to traditional finance.

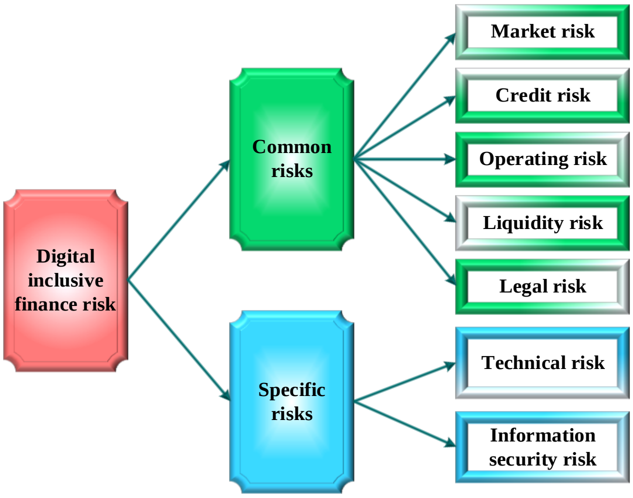

Fig. 1. Risk types of digital inclusive finance.

The common risks related to digital inclusive finance are depicted in Fig. 1, including market, credit, operating, liquidity, and legal issues. Additional unique hazards include those related to technology and information security [25-27]. In order to serve borrowers with less-than-ideal credit histories who have restricted access to conventional financial services, inclusive finance products often comprise unsecured small credit loans. As a result, the main risk for digital inclusive finance is the credit risk associated with the borrowers. Market risk is most often used to describe the potential for financial asset losses brought on by unfavorable changes in market prices, including interest rates, exchange rates, stock prices, and commodity prices. Financial institutions that embrace digital technology receive most of their funding from shareholders and a smaller amount from the securitization of financial assets. Digital inclusive financial institutions that specialize in small and microloans may be exposed to liquidity concerns due to insufficient funding sources, which could interrupt their business and result in large financial losses. The potential loss brought on by operational mistakes in financial transactions is known as operating risk. It relates to both risks brought on by ineffective staff operation and instrumental risk. The absence of well-defined legal regulations and ambiguous regulatory contexts, which can have a negative effect on platform economic operations, are the main sources of the legal risk associated with digital inclusive finance. Technical concerns can quickly arise because digital inclusive finance is a relatively young field and the use of digital technology is not yet fully developed. The information security risk associated with digital inclusive finance refers to the inability to protect customer information due swiftly and effectively to problems including flawed systems and the neglect of security flaws in the transmission, usage, storage, and eradication of information. These dangers can result in the theft, alteration, abuse, and disclosure of consumer information, thereby resulting in customer losses.

3.3 Credit Risk Assessment of Digital Inclusive Financial Platform Based on BP-KMV Model

The KMV model proposed by the KMV Company in San Francisco, USA, is primarily utilized to assess the credit risk of listed companies [28]. This paper selects M company, a non-listed company that does not have objective market value indicators such as stock price fluctuations, as an example for analysis. Listed companies are adopted as the basic sample to construct a Back Propagation (BP) neural network model to predict the credit risk of M company [29]. Fig. 2 depicts the working principle of the constructed BP-KMV model.

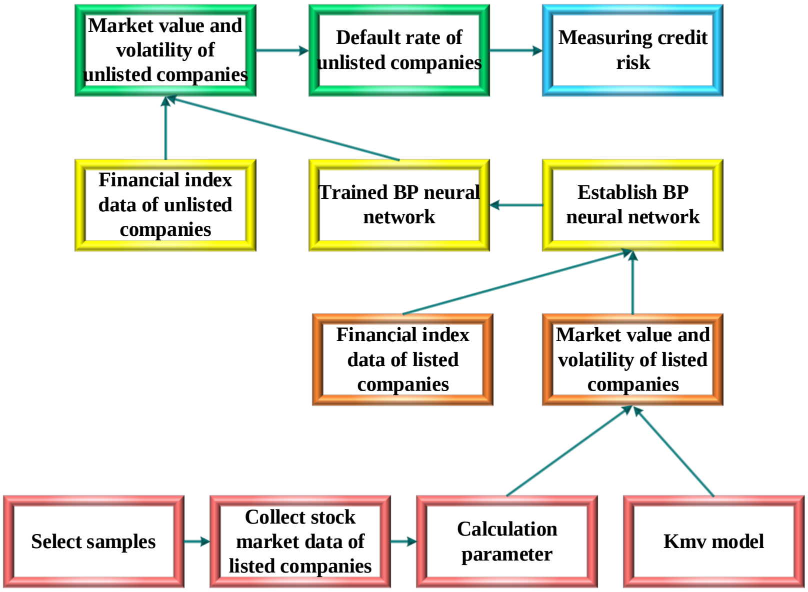

Fig. 2. Working principle of the BP-KMV model.

The steps of the BP-KMV model are shown in Fig. 2. First, a sample of listed firms with digital inclusive financing that are comparable to M company is chosen. The reason for this is that businesses in the same industry will face comparable credit risk circumstances. Next, information on listed firms' stock markets is gathered, including stock market value, stock price volatility, default point, risk-free interest rate, and estimated lifespan. The KMV model is used to calculate the market value and volatility of listed firms [30]. Then, as input variables, the major financial indicators of listed firms are used. These indicators include the ratios measuring operational efficiency (total assets turnover and return on total assets), profitability (operating profit rate), liquidity (quick ratio), solvency (debt to asset ratio), and growth potential (net profit growth rate). As output variables, the market value and volatility of listed firms are used. After that, the BP model is built and trained [31]. Input signals are sent from the input layer to the hidden layer, then to the output layer in BP neural networks. A single hidden layer is established, along with an input layer and an output layer, resulting in a three-layer neural network structure [32]. Additionally, the six financial indicators gathered above are used as input signals, and the output signals are the calculated asset value volatility and asset value logarithmic value. A BP neural network model is created, with the hidden layer's number of neurons set to 10, as shown in Fig. 3 [33-35].

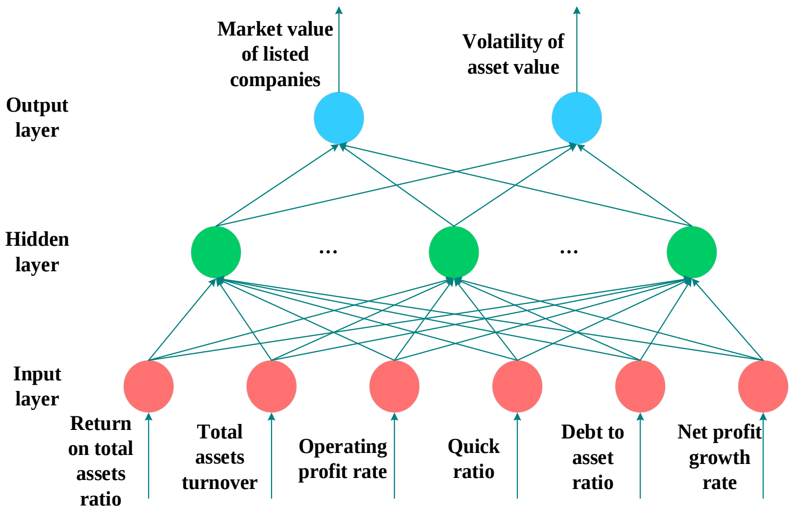

Fig. 3. BP neural network constructed with financial indicators as input.

After constructing the BP neural network, the selected samples are utilized. A trained neural network is obtained by constantly changing the ratio of the number of training samples to the number of test samples. Finally, major non-listed financial indicators such as M company are imported, and their market values and volatility are output through the trained BP model to measure their credit risk. Four unlisted companies, including Ant Group, are taken as model-solving samples in 2019. The same six financial indicators from these four companies in 2019 are inputted, and the asset values and volatility of the four companies are simulated. The KMV model, which is used for solving listed companies, is applied to incorporate the calculated asset values and volatility of these unlisted companies. The default distance for non-listed companies like Ant Group is calculated and subsequently converted into a default rate.

4. ANALYSIS OF EXPERIMENTAL RESULTS

4.1 Case Introduction and Training Sample Selection

This paper takes M company as a case study for analysis. The company was born in the early 21st century and started in 2004, the early stage of the development of the e-commerce industry. It was officially established in October 2014. M company is committed to inclusive finance and has a leading level of financial technology. Its primary operations are conducted through the Alipay platform, where it offers a diverse range of services. M company is the first to occupy the third-party payment market. Since 2015, it has cooperated with multiple countries and regions to develop digital wallets. Then, it lays out its small loan business, which has become its main income and profit source. Currently, M company mainly carries out business on the Alipay platform, which is divided into microloan technology, digital payment, wealth management technology and insurance technology. Among them, microloan technology includes Ant Credit Pay and Ant Cash Now, wealth management technology includes Ant Wealth and Yu'E Bao businesses, and insurance technology includes Mutual Treasure, Good Medical Insurance, and Ant Insurance businesses.

The constituent stocks of the National Securities Xiangmihu Financial Technology Index (399699.S) are taken as the scope of training sample to select companies involved in inclusive financial business. 34 companies listed before 2019 are selected as the final research sample. All empirical analysis data are sourced from the Wind database. Most of these companies are situated in developed cities like Beijing, Shanghai, Guangzhou, and Shenzhen. They have been listed for a considerable period and primarily focus on providing financial technology services. The main business of M company is the same as them, indicating that the sample selection is more reasonable. Subsequently, the original data of 34 digital inclusive financial companies, including the stock closing price, the number of outstanding shares, basic earnings per share, net assets per share, and liabilities, are utilized. The purpose is to calculate the five parameters required for the model: stock market value, stock price volatility, default point, risk-free interest rate, and expected life. The KMV model is applied to calculate the market value and volatility of the company's assets through the market value and volatility of the company's stock. Then, the default distance and default rate of listed companies are calculated to verify the utility of the KMV model. Finally, the trained BP neural network is employed to solve M company's market value and volatility.

4.2 Experimental Environment

The operating system used in this study is a 64-bit Windows10 system. The Central processing unit (CPU) is Intel(R)Core (TM)i7-7700. The main frequency of the CPU is 3.60GHz, the memory is 16GB, the graphics card is NVIDIA GeForce GTX 1080×4, the storage hard disk is 5.2T, and the video memory is 8GB. The network model is built using python3.9 programming language and pytorch1.10.0 deep learning framework.

4.3 Hyperparameters Setting

In the experiment, BP neural network has one hidden layer. The collected total assets turnover rate and total assets return rate, operating profit rate for profitability, quick ratio for liquidity, asset-liability ratio for repayment ability, and net profit growth rate for growth ability are used as input signals, and logarithmic index of asset value and volatility of asset value are used as output signals. The number of neurons in the hidden layer is set to 10, the initial learning rate is 0.001, and the ReLU activation function is used.

4.4 Data Analysis of Training Samples

Fig. 4 displays the stock market value and asset value data of listed companies obtained through the KMV model. Fig. 4 reveals that there is no significant positive and negative relationship between the asset market value and its volatility of digital inclusive finance listed companies. Additionally, the average volatility of the asset market value of the selected digital inclusive finance listed companies is 45.37%, reflecting that their asset value is not very stable.

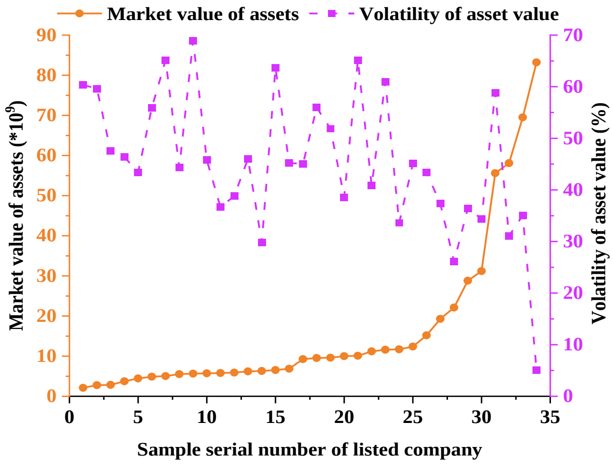

Fig. 4. Market value and volatility of assets of listed companies.

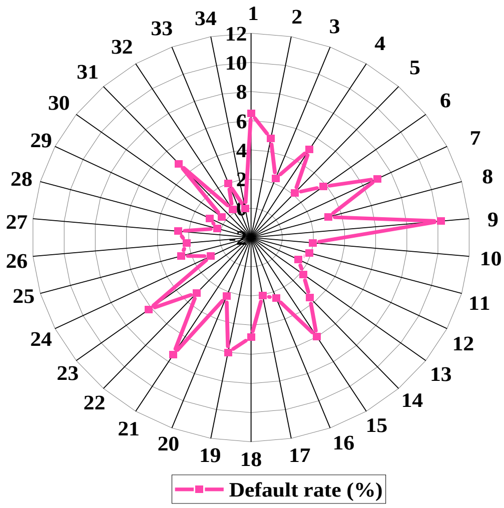

Fig. 5. Default distance and default rate of listed companies.

Fig. 5 suggests that the average default rate of listed companies of digital inclusive finance is 3.34%, and serious polarization exists. The minimum default rate is 0.04%, while the maximum reaches 10.19%. Five listed companies numbered 14, 17, 30, 32, and

33 are randomly selected, with default rates of 3.58%, 2.06%, 0.33%, 0.25%, and 1.98%, respectively. According to the “Qi Cha Cha”, the credit ratings of the five companies (entities) numbered 14, 17, 30, 32, and 33 are AA–, AA–, AA, AA+, and AA+, respectively. The default rates calculated by the BP-KMV model are ranked from largest to smallest as No. 14, No. 17, No. 32, No. 30, and No. 33, which are basically consistent with the credit rating results. This reflects the credibility of the BP-KMV model in measuring corporate credit risk.

4.5 Credit Risk Assessment of M Company

The trained BP neural network model is used to solve the market value and volatility of four unlisted companies: M company, L company, W company and J company. The results are shown in Fig. 6.

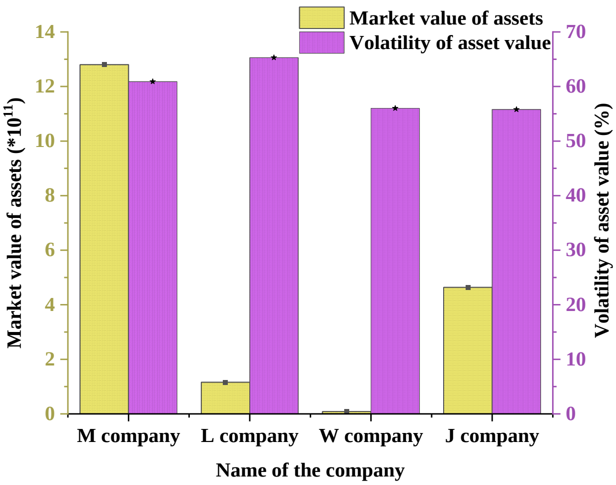

Fig. 6. Market value and volatility of assets of four non-listed companies.

Fig. 6 shows that the asset market value of M company exhibits the highest among the four non-listed companies, while L company experiences the highest volatility of asset value, reaching 65.28%. This indicates no significant correlation between the asset market value and the volatility of non-listed companies’ digital inclusive financial platforms. Additionally, the average asset value volatility of these four non-listed companies is 59.495%, which exceeds the average observed in the listed companies mentioned earlier. This indicates that non-listed companies may face greater operational instability.

The BP-KMV model is employed to solve the default rates of four non-listed companies. Fig. 7 presents the results. Fig. 7 indicates that the default rate of M company is 6.12%, higher than 4.82% and 4.84% of J company and W company, while lower than 7.35% of L company, reflecting the high credit risk of M company. The default rate of M company and the default rate of the listed companies mentioned above are ranked. The relatively low ranking of M company further reflects that M company has a high credit risk in the digital inclusive finance industry.

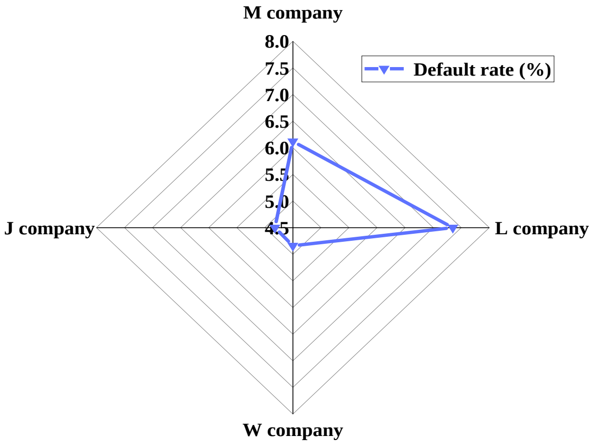

Fig. 7. The default rate of four non-listed companies.

4.6 Analysis of Digital Inclusive Financial Risk Control of M Company

Aiming at the digital inclusive finance risk control of M company, it is carried out from two aspects: the relationship between its risk degree and R&D capability, and the advantages and disadvantages of risk control technologies such as big data technology, blockchain and artificial intelligence (AI). First, the relationship between M company's risk level and R&D capabilities is compared. Fig. 8 displays the R&D capabilities of four non-listed companies.

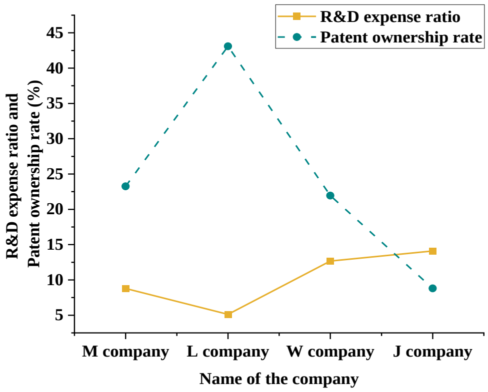

Fig. 8. R&D capabilities of four non-listed companies.

Fig. 8 suggests the R&D capabilities of the four non-listed companies. Among them, J company has the highest R&D expense rate at 14.1%, while L company has the highest patent ownership rate at 43.09%. According to Fig. 8, there is a negative relationship between the default rate and the R&D expense rate among the four companies. A higher default rate is associated with a lower R&D expense rate. Conversely, a positive correlation is observed between the patent ownership rate and the default rate. A higher patent ownership rate corresponds to a higher default rate.

Besides, the risk control results of M company are analyzed from risk control technologies such as big data technology, blockchain, and AI. Table 1 shows the advantages and disadvantages of various risk control technologies.

Table 1. Advantages and disadvantages of M company's risk control technology.

Risk control technology	Advantages	Disadvantages
Big data	Optimize memory, improve operational efficiency, and reduce information security risks	Incomplete information collection and deviation in risk identification results
Blockchain	Effective retention of certificates of deposit, timely tracking of the source of abnormal behavior, and reducing credit risk	Requires huge storage space and strong encryption technology
AI	Quickly identify risks, improve risk control decisions, and reduce human errors	High cost and equipment requirements
Shared intelligence	Improve the accuracy and performance of risk control	Incomplete sharing sources and distorted data information

Table 1 shows that the shortcomings of blockchain technology can be remedied by big data technology, using efficient storage to solve the problem of large blockchain storage. Shared intelligence technology can improve the closed information source of big data. The collaborative operation of big data, blockchain, and shared intelligence fosters the improvement of artificial intelligence, reflecting the promotional effect between M company's risk control technology.

In addition, the risk prediction accuracy of BP neural network and BP-KMV model is compared. The BP neural network model and the proposed BP-KMV model are used for prediction on the same test sample dataset. Their prediction performance is evaluated by analyzing the absolute error between the predicted values and the actual evaluation values and the prediction accuracy of the two algorithms. Fig. 9 presents the results of the prediction performance analysis for different algorithms.

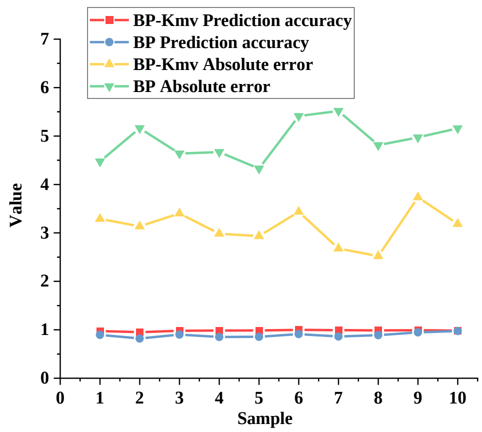

Fig. 9. Prediction performance analysis results of different algorithms.

It can be observed from Fig. 9 that the BP-KMV neural network algorithm has small absolute errors, all of which are below 4. In addition, the risk prediction accuracy of BP-KMV model is above 0.932, while the risk prediction accuracy of traditional BP neural network model is worse than that of BP-KMV model.

4.7 Discussion

To sum up, BP-KMV neural network based on AI has better performance in predicting enterprise credit risk, and it is compared with other similar studies. Mijwil *et al.* (2023) pointed out that artificial intelligence utilized customer-provided privacy data such as faces and fingerprints to accurately identify customer risks and reduce operational risks associated with subjective human judgments [36]. Jang *et al.* (2022) argued that, starting from the currently mastered technologies, big data, blockchain, and artificial intelligence mutually promoted each other, enhancing risk control capabilities. However, the high cost of implementing new technologies may not be suitable for small-scale digital inclusive financial institutions. Furthermore, based on the analysis of credit risk using the BP-KMV model, it is found that Ant Group's credit risk is at a relatively high level. It is possibly due to insufficient technological investment that hampers the effective maintenance of the risk control system, thus weakening Ant Group's credit risk control capabilities. However, the significance of this relationship has not been fully demonstrated due to the small sample size [37]. The research findings are generally consistent with those of Ye *et al.* (2022) [38]. Wan and Yu (2023) analyzed the financing risk, investment risk, capital operation risk and growth risk faced by enterprises under the requirements of low-carbon economy development from the perspective of low-carbon economy. On this basis, a financial risk management framework with clear hierarchy and strict vertical logic is constructed, and the risk prediction model of the index system is established by using BP neural network. The results show that the accuracy of the model reaches 84.3%, and it is in line with the requirements of low-carbon economic development to include "low-carbon" in the design of enterprise financial risk early warning indicators [39]. In a word, more and more studies show that neural network and AI have great potential in predicting enterprise risks.

5. CONCLUSIONS

The paper examines big data risk control technologies against the backdrop of smart cities to research the risk control of digitally inclusive financial platforms. Financial data from listed firms are used as training samples for a BP-KMV model that is built using the default prediction KMV model and BP neural network. The following conclusions are reached after studying the credit risk and risk management of an unlisted M company on the digital inclusive financial platform: (1) According to the "Qi Cha Cha", the randomly selected companies (entities) numbered 14, 17, 30, 32, and 33 have credit ratings of A−, AA−, AA, AA+, and AA+, respectively. The default rates calculated by the BP-KMV model are ranked from largest to smallest as 14, 17, 32, 30, and 33, with 3.58%, 2.06%, 1.98%, 0.33%, and 0.25%, respectively, which is basically consistent with the credit rating results. It reflects the credibility of the BP-KMV model in measuring corporate credit risk; (2) The default rate of non-listed companies has a negative relationship with the R&D

expense rate. A lower R&D expense rate corresponds to a higher risk of default. Conversely, a positive relationship exists between the patent ownership rate and the default rate, with a higher patent ownership rate associated with an increased default rate; (3) The risk control technologies of M company promote each other. Big data technology addresses the limitations of blockchain technology, enabling efficient storage to overcome the challenges of large blockchain storage. Shared intelligence technology can improve the situation where the information source of big data is closed. AI can advance thanks to the co-operative use of big data, blockchain, and shared intelligence. There are still some issues with the research though. Only 34 small training samples are used, which could cause instability in the BP neural network model. Future study should think about increasing the size of the training sample or creating a more stable DNN model to get more accurate findings.

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Wei Shi received an MS degree in Education Management from Guangxi Normal University in 2019. In 2020, he was appointed as an Associate Professor at Guangxi Banking School. His primary research interests focus on Financial Technology and Inclusive Finance.

Si-Qi Long received an MS degree in Education Management from Guangxi Normal University in 2018. Since 2008, he has been serving as a teacher at Guangxi Banking School. His primary research interest lies in the application of information technology in management.

Yue Li received his MS degree in Finance and Management, Loughborough University, UK, in 2014. Since 2016, he was appointed as a Lecturer at Guangxi Financial Vocational College. He is currently a Ph.D candidate in Finance at Universiti Putra Malaysia, Malaysia. His primary research interests concentrate on banking and microfinance.