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Artificial Intelligence Application and Corporate Financial Distress

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Abstract:
With the increasingly changeable external environment, enterprises face the threat of crisis at any time and may be in financial distress. The development of new technologies in the era of artificial intelligence (AI) provides new ideas and methods for enterprises to alleviate financial distress. We will study whether AI technology can resolve the financial distress of the enterprises, and what is the impact mechanism. Through the empirical tests of Chinese listed companies, we find that AI technology can alleviate the financial distress of enterprises by improving the resource acquisition ability and risk management ability, and the heterogeneity tests find the effect of AI technology is better when the supply chain network more dispersed, the corporate governance environment better, as well as the enterprises controlled by state-owned property rights. So enterprises should increase the research and development of AI technology application, improve corporate governance to promote the effect of AI technology greater, as well as use AI technology to provide references and advices for managers' decision-making. We enrich the theoretical research of AI in the field of financial management, and provide new ideas for companies to alleviate financial distress in practice.

Keywords:
Artificial Intelligence; Financial Distress; Resource Acquisition Capability; Risk Management Capability; Corporate Governance

1 Introduction

Nowadays, business environment is increasingly complex and changeable. With the globalization and internationalization of business activities, crises seem to have become a regular event in organizational development. For example, the global COVID-19 epidemic, war, anti-globalization trend has caused the global economic and political turmoil, these "black swans" (low probability but high impact events) or "grey rhinos" (high probability and high impact potential crises) pose increasing challenges to the survival and development of organizations, Enterprises need to improve their abilities to deal with adversity events and get rid of financial difficulties in time to achieve long-term sustainable development. Financial distress, default and bankruptcy are the basic life stages of listed companies. Trying to resolve financial distress is the survival instinct of distressed companies to avoid the realization of default and bankruptcy. On the study of financial distress, scholars mainly conduct from the perspectives of financial distress warning, financial distress measurement, financial distress affecting factors, etc. For example, companies with steady investment and rapid growth of

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sales, companies that pay attention to external market and long-term growth are more likely to get out of financial difficulties (Schendel & Patton,1975; Sudarsanam & Lai,2001). Factors such as the degree, mode and time of corporate mismanagement, internal organizational structure, market competition position and industry economic environment also affect the degree of corporate financial distress (Hofer,1980; O'Neill,1986; Opler & Titman,1994). In the era of AI, the emergence of new technologies provides new opportunities and ideas for companies to get rid of financial difficulties.

In the last decade, big data and AI technologies have continued to produce revolutionary innovations, and intelligent algorithms have undergone significant and advanced development. China has set AI as the major national strategic direction, and the field of information systems is facing a series of new development opportunities and profound challenges, transforming from digitization to intelligence gradually, high-level intelligent algorithms will become core competencies and competitive advantages. Although the acquisition of big data has become possible, but the data that people can process directly is often limited and partial. Therefore, AI technology is needed to convert big data into small data for analysis, and help managers to make decisions as soon as possible (Milojevic & Redzepagic,2021). In the era of comprehensive application of digital and intelligent technologies such as big data, AI, blockchain, and the Internet of Things, the speed and efficiency of enterprises' information acquisition has improved greatly, the trust relationship between organizations can be established easily, the problem of information asymmetry is alleviated, and enterprises can obtain information through massive amounts of data analysis, risks can be found and dealt in time, and external resources from supply chains, banks, governments and other organizations can be obtained quickly, the efficiency of corporate governance can also be improved greatly, bringing new opportunities for corporates to alleviate financial difficulties.

At present, the research of AI technology in financial management mainly focuses on how to use technologies of decision tree, text analysis, machine learning and other technologies for price and cost forecasting, risk warning, performance forecasting, financial fraud identification, financial decision-making , etc, mainly use model construction, case analysis, simulation test and other methods, and there are not many papers using regression tests with large samples(Zhu et al.,2022; Nti et al.,2020; Michaels & Gruening,2017; Hajek & Henriques,2017; Hsu et al.,2018).The researches on whether AI technology can alleviate corporate financial distress and the effect mechanism are not sufficient, we will use the data of Chinese listed companies to test the impact and mechanism of AI technology application on financial distress, and use heterogeneity tests to find out factors that can improve the effect of AI applications.

The innovations of this paper are as followed: Firstly, previous researches mainly focus on the designs and models of AI technology, there are relatively few studies on how companies can use AI technology to alleviate financial distress; Secondly, The impact mechanism of AI technology on the financial management application in enterprises is still unclear, we study the mechanism from the perspectives of enterprises' resource acquisition ability and risk response ability; Thirdly, we study how to improve the application effect of AI technology from the perspectives of supply chain concentration, corporate governance and property rights, enriching the optimization countermeasures of AI application.

The main reasons for using Chinese data for this paper are as followed: Firstly, China has strong national policy support for AI technology, and many companies have used AI technology for operations, so we can use

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large samples for research; Secondly, China has a large amount of state-owned enterprises, the nature of the property right is special, we can compare the effect of AI technology under different property rights; Thirdly, many Chinese enterprises are affected by the Covid-19 and the unfavorable international environment, facing serious financial difficulties, it is suitable for us to test the effect of AI technology application in alleviating the financial distress in this unfavorable environment.

The structure of this paper is arranged as followed, the second part discusses the application background and development practice of AI, the third part proposes the research hypothesis, the fourth part is the data and research model, the fifth part is the results of empirical tests, and the sixth part proposes conclusions and discussions for companies.

2. The application background and development practice of AI

Artificial intelligence has developed from laboratory to application in various industrial practice fields, showing a vigorous development trend (Reier Forradellas & Garay Gallastegui, 2021). In the era of digital intelligence, while empowering traditional industries, AI technology has also been integrated with the networked resource carried by Internet platforms deeply. Based on machine learning, intelligent data mining, natural language processing and other technologies, AI has provided technical and organizational support for the automatic production, automatic decision-making and automatic sales, “intelligent robot” has also become a new “behavior subject”. The intelligent development of enterprises has received extensive attention from scholars in recent years, intelligence can promote supply chains’ coordination and sustainable development (Ghadimi et al.,2019), transform the mode of economic development (Kalenyuk et al.,2021), improve the total factor productivity of manufacturing(Sun & Zhong,2020), promote regional economic transformation (Cai,2022), promote disruptive innovation of enterprises, and improve enterprise performance (Yang et al.,2020; Czarnitzki & Kraft,2004).

AI applications include automated analysis, visual reporting, intelligent robots and so on, all of the tools allow individuals to understand their environment better and act accordingly, give full play to its potential by optimizing existing processes and increasing automation, as well as detecting and predicting the abilities of interacting with humans. AI can increase the efficiency of supply chain operations and maintenance, optimize and improve customer experience, improve products and services, improve the adaptation to the changeable market conditions rapidly and automatically, create new business models, and optimize the relationship with suppliers and customers with better forecasting and planning capabilities (Wamba-Taguimdje et al.,2020). AI technology has entered financial management applications gradually, but they are still in their early stages, they are mainly used in processes such as billing, intelligent reporting, intelligent identification, intelligent audit, automatic payment and so on (Polak et al.,2020). AI has transformed from the pursuit of “computer simulation of human” to the construction of self-learning, self-adaption, and self-organizing capabilities, becoming an intelligent system composed of machines, people, networks, materials, and data . In the future, AI technology needs to be applied to the field of accounting robots and financial robots, it can realize automatic bookkeeping, process all accounts, realize analysis, planning, control, prediction, simulation, and other intelligent management based on the understanding of various accounting standards, financial management systems and laws.

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Scholars mainly study AI from practical applications, such as how to use decision trees, deep learning, genetic algorithms, neural networks, machine learning, convolutional neural networks and other AI methods to predict prices, estimate costs, monitor risks, and predict corporate behavior better.

AI technology is good at predicting prices and estimating costs. For example, predicting crude oil prices, iron ore prices, and estimating oilfield development costs (Wang et al.,2018; Li et al.,2020; Mingyu et al.,2021).

AI technology can predict and control risks, including estimating corporate credit fraud risks to reduce economic losses effectively, estimating market systemic risks and help decision makers deal with systemic risks, estimating tax risks to support tax authorities in detecting tax evasion and avoidance, predicting stock market crisis events (Li & Li,2019; Yu & Zhao,2020; Didimo et al.,2020; Chatzis et al.,2018).

AI technology can monitor corporate crises, such as building models to predict bankruptcy risk, estimating corporate risk defaults, predicting credit risk, predicting financial distress, predicting corporate bankruptcy, monitoring financial fraud, and predicting business failure, AI technology can improve the prediction accuracy(Hajek & Henriques,2017; Zhao et al.,2017; Kim & Cho,2019; Moscatelli et al.,2020; Zhu et al.,2016; Ma & Lv,2019; Bae,2012; Barboza et al.,2017; Lourdes Borrajo et al.,2011).

AI technology can predict corporate performance and help companies make better decisions, such as predict financial risk behavior, predict profit, predict earnings per share, and predict stock prices (Kim et al.,2020; Song et al.,2018; Chang et al.,2018; Etemadi et al.,2015; Hagenau et al.,2013; Rajab & Sharma,2019)..

AI technology can help companies make better decisions and governance, it can identify financial statement fraud, build predictive decision support system, build stock decisions, help to do portfolio selection, build e-commerce platform, build financial decisions, reduce financial risk, improve smart contract efficiency (Chatzis & Siakoulis & Petropoulos & Stavroulakis & Vlachogiannakis,2018; An & Suh,2020; Chan & Franklin,2011; Lee et al.,2019; Magoc & Modave,2011; Li,2020; Drezewski et al.,2018; Zhao,2021; Cunha & Silveira,2020).

However, previous researches mainly focused on model construction, conceptual assumptions, future prospects, etc. The application effect and mechanism of AI technology in practice need to be tested further. We study how AI technology affects the financial distress of enterprises, and examine the mechanism from the prospectives of resource acquisition ability and risk management ability. Heterogeneity tests are carried out from the perspectives of supply chain relationship, corporate governance environment and property rights, which enrich the researches of AI in the field of financial management, as well as providing reference suggestions for enterprises to apply AI technology better.

3. Research Hypotheses

When companies face difficulties, they are more likely to default. At this time, companies need to manage existing resources, assess and control risks better in order to alleviate financial difficulties in time. AI uses technologies such as data analysis, network search, and machine learning to collect internal and external relevant data quickly, mine the internal relationships of data, help companies assess risks, find opportunities, and

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reduce the possibility of corporate defaults better.

Firstly, enterprises using AI technology can help them obtain more external resources, AI equipment generates a large number of transaction data, which can help enterprises obtain bank loans as digital assets (Qureshi,2020; Mhlanga,2020), at the same time, AI technology can help enterprises build ecosystems, share data with banks, suppliers, customers, etc., reduce information asymmetry between enterprises and outsiders, which can alleviate the financial difficulties of enterprises. Secondly, AI technology can enable enterprises estimate, control and supervise the company's risks reasonably, take measures timely to deal with the risks before they come, and make reasonable countermeasures when facing crises (Zhu et al.,2022). Thirdly, AI technology can reduce the irrational behaviors of decision makers, for example, under the application of AI technology, enterprises will not overestimate future income, and they will be more cautious when investing, reduce the inefficient investment behavior of corporate executives and make investment decisions more accurate(Bhatia et al.,2020); AI can make asset evaluation, pricing and cost estimation more reasonable, and reduce mistakes of executive decision-making(Fu et al.,2017); in the process of financing, financial risks can also be estimated reasonably, so that the companies will not face excessive financial leverage, they will control risks, and the possibility of corporate defaults is lower. Fourthly, with the use of AI technology and the popularization of internet thinking, the information disclosure, corporate governance mechanism and supervision systems of enterprises tend to be scientific and precise, all aspects of corporate governance are more prone to improve through data mining and analysis. The implementation of big data and artificial intelligence not only helps to improve the information disclosure quality and information transmission efficiency, but also helps to form a corporate governance system based on data mining, analysis and application gradually. Managers rely more on quantitative analysis of data than subjective judgment (Lee et al.,2019; Ta et al.,2020; Gadzinski et al.,2022). Thus, it can reduce its discretion, alleviate the principal agent problem, and make correct decisions to alleviate financial difficulties. Therefore, we propose Hypothesis 1.

H1: AI technology can alleviate corporate financial distress

AI technology can help companies obtain more external resources. Using AI technology can reduce information asymmetry among enterprises, banks, governments, and external investors. Enterprises can share data by establishing data interfaces, and use automated software to generate real-time data analysis, help external stakeholders understand the companies' conditions better. In this way, enterprises can improve their abilities to obtain external resources and alleviate their financial difficulties. AI can overcome the problem of information asymmetry (Kaya & Pronobis,2016). Digital inclusive finance can realize through AI by connecting to various platforms and networks, generating a large amount of information, which can be used as an important digital resource for enterprises to pledge loans from banks (Qureshi,2020). Digital tools based on big data analysis and cloud computing can establish a credit scoring mechanism to help companies improve their credit levels and obtain more loans (Mhlanga,2020), improving the loan capacity from banks can help enterprises alleviate financial crises in difficult times.

In addition, AI technology improves the resource allocation efficiency of enterprises, so that existing resources can be utilized fully. Intelligent technology reduces the use of low-skilled labor, and relies more on capital and skilled labor, production factors can be used more efficiently. Therefore, intelligence can improve capacity utilization effectively (Graetz & Michaels,2018). Based on the theory of comparative advantage, the

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main purpose of implementing intelligence in enterprises is to promote specialized production, reduce labor time and labor costs, improve labor productivity (Acemoglu & Restrepo,2018), reduce average costs, expand enterprise scale, and form a “economies of scale” and “economies of scope”. Intelligence can also improve the technological innovation of enterprises, ensure the sustainable corporate development, improve market competitiveness, and capture high profits (Clarke et al.,2011). AI technology can improve the work efficiency of enterprises and reduce the processing time of complex work. Enterprises can have enough time and energy to find the resources at their disposal and look for new opportunities. At the same time, enterprises can improve the efficiency of resource allocation by using data analysis technology, help enterprises overcome difficult times, reduce default risks, and alleviate financial distress.

Under the circumstance that it is difficult for enterprises to obtain external resources, the advantages of AI will be more obvious. We will analyze from the prospects of financing constraints and government subsidies. Banks and the government are important ways for enterprises to obtain resources. When the enterprises’ resource acquisition ability is poor, then their financial constraints are higher and government subsidies are lower. When it is difficult for enterprises to obtain such external resources, the use of AI technology can help enterprises manage existing resources better, make more accurate decisions, reduce irrational behavior, and the asymmetry problem can be reduced by improving the degree of information sharing with the outsiders, help enterprises obtain external financing as soon as possible, and alleviate financial difficulties. Therefore, we propose Hypothesis 2.

H2: The worse the enterprise’s resource acquisition ability, the better the effect of AI technology to alleviate corporate financial distress.

When the enterprise’s risk level is high, the application of AI technology can help the enterprise deal with the risk better. For example, enterprises can use real-time data analysis systems to know the current situation, make timely decisions, and use AI technologies such as data mining and analysis, deep learning, and network search to predict the risks that enterprises may face, and avoid them in time(Zhu et al.,2016; Bussmann et al.,2021; Coser et al.,2019). Therefore, we believe that the higher the enterprise risk, the more obvious the advantages of AI technology, and the better the effect of alleviating corporate financial distress.

Enterprises can use data mining and analysis, deep learning, web search and other methods to improve their risk response abilities. Data mining and analysis technology can realize the analysis and mining of a large amount of financial and non-financial data, and improve the efficiency of risk prediction and prevention through visual charts (Divsalar et al.,2012; Khemakhem et al.,2018). Web search can enrich the database continuously through the collection of Internet data, which may include data of the company itself, upstream and downstream enterprises in the supply chain, competitors, potential consumers, etc. The company uses the searched data to make analysis so as to improve the accuracy of financial risk warning, and achieve the purpose of risk prevention and control (Wang, 2018). Deep learning establishes an analysis model by judging the deep rules of a large number of data, and then realizes multi-level correlation analysis through the input of information from different sources, so as to improve the financial analysis ability and deductive reasoning ability, which can provide supports for managers’ decisions (Du & Shu,2022; Maratkhan et al.,2021).

We will analyze from three aspects: operational risk, financial risk and liquidity risk. The unstable opera-

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tion of the company will affect the company's ability to operate continuously. Financial risks may make the company unable to repay its debts in time and lead to bankruptcy. Liquidity risk is affected by the company's cash flow, when the company does not have sufficient cash flow to repay debts, there will be a bankruptcy crisis. Using AI technology, it is possible to monitor the operation, financing, and cash flow of the company in time, observe the transaction status of upstream and downstream companies in the supply chain, analyze the financial risks of the company, and give early warning when the company is over-financing. When there is insufficient cash flow, it can remind managers to supplement working capital timely, warn before risks and monitor when facing risks, ensuring stable operation of enterprises, reducing the default risk, and alleviating financial difficulties of enterprises. Therefore, we propose hypothesis 3.

H3: The higher the operational risk, financial risk, and liquidity risk of the enterprise, the better the effect of AI technology on alleviating corporate financial distress.

4 Data and Model

In this section, we discuss the data and model for empirical tests in detail.

4.1 Variable Definitions

(1) Explained variable

The explained variable is corporate financial distress. We use the KMV model to calculate the default distance, which can measure the corporate financial distress. The model treats defaulted debt as the contingent interest of the company, owner's equity as a call option, debt as a put option, and company assets as the underlying assets. The model believes that corporate credit risk is mainly determined by the market value of corporate assets, volatility and book value of debt. The larger the default distance is, the stronger the ability to repay the debt when due, the smaller the default probability and financial distress will be.

Firstly, we use the Black-Scholes option pricing model to estimate the market value of the stock and its volatility. E is the value of equity, DP is the default point, as well as the critical point of financial distress, which is defined as DP=SD+0.5×LD , SD is the short-term debt of the company, LD is the long-term debt of the company. V is the market value of the company's assets, T is the maturity of the debt, set to one year, is the volatility of the company's asset value, and r is the risk-free interest rate, is the volatility of the equity value .We calculate the market value (V) and volatility () of corporate assets according to the following set of simultaneous equations.

$$\begin{cases} E=V\times N(d_1)-DP\times e^{-rT}\times N(d_2) \\ \sigma_E=\dfrac{N(d_1)\times V\times \sigma_a}{E} \end{cases} \quad (1)$$

$$d_1=\frac{\ln(\frac{V}{DP})+(r+0.5\times\sigma_a^2)\times T}{\sigma_a\times\sqrt{T}},\ d_2=d_1-\sigma_a\times\sqrt{T} \quad (2)$$

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Secondly, after obtaining the market value (V) and volatility (σ_a) of corporate assets, we calculate the company's default distance DD, E(V) is the expectation of the company's asset value.

$$DD = \frac{E(V) - DP}{E(V) \times \sigma_a} \quad (3)$$

Finally, we calculate the probability of default (EDF), N (•) is the standard normal distribution function. The higher the default probability EDF is, the higher the risk of debt default, and the more serious the financial distress will be.

$$EDF = N(-DD) \quad (4)$$

(2) Explanatory variable

The explanatory variable is AI technology application. We conduct a text search on the annual report information of listed companies. If the word of "artificial intelligence" appears more than 3 times, the variable takes 1, otherwise takes 0.

(3) Moderator variables

(i) Resource acquisition ability. We use government subsidies and financial constraints to measure the resource acquisition ability. The more government subsidies obtained, the less financial constraints, then the stronger the resource acquisition ability. Government subsidies are measured by dividing the amount of government subsidies by operating income. The degree of financial constraint is measured by the WW index and the KZ index. This paper refers to the financial constraint measurement method of Whited & Wu(2006), and uses Chinese data to construct the *W index =0.1292255×Size+0.2806241×CF+0.0657391×Growth+0.5100916×ISG - 1.572105×Lev_ind+0.4936025×TLTD - 0.3375704×Current*, where *Size* is the natural logarithm of total assets; *CF* is ratio of cash flow from operating activities to total assets; Growth is the company's actual revenue growth rate; *ISG* is the industry revenue growth rate; *Lev_ind* is the mean of Lev in industry; *TLTD* is the ratio of long-term interest-bearing liabilities to book assets, *Current* is liquid assets. We construct the *KZ* index with Chinese data referring to Kaplan & Zingales(1997). *KZ* index= *- 14.21684×CF- 7.243019×CASH - 5.032141×DIV+0.4365548 ×TobinQ+3.861434×Lev,* where *CF* is the ratio of cash flow from operating activities to total assets, *CASH* is the ratio of cash holdings to total assets, *DIV* is the ratio of cash dividends to total assets, *TobinQ* is the asset market value divided by asset book value, *Lev* is the ratio of total liabilities to total assets. In addition, we conduct the cash-cash flow sensitivity test on the recalculated *WW* index and *KZ* index. It is found that the larger the *WW* index and *KZ* index, the higher the cash-cash flow sensitivity, which proves that it is reasonable to use the *WW* index and *KZ* index to measure the degree of financial constraints.

(ii) Risk level. We measure risk from three aspects: operational risk, financial risk and liquidity risk. The operational risk is the standard deviation of *ROE* within three years, the financial risk is the level of excessive debt, and the liquidity risk is measured by the current ratio. Excessive debt level is calculated by using the actual capital structure minus target capital structure. The target capital structure is shown in formula (4), where *Lev* is the actual capital structure, *State* is the nature of property rights, *ROA* is the return on total assets, and *Lev_IND* is the median of capital structure in industry, *Growth* is the revenue growth rate, *TA* is the proportion of fixed assets in total assets, *Size* is the natural logarithm of total assets, and *First* is the largest shareholding ratio..

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$$Lev_t = a_0 + a_1 State_{t-1} + a_2 ROA_{t-1} + a_3 Lev_IND_{t-1} + a_4 Growth_{t-1} + a_5 TA_{t-1} + a_6 Size_{t-1} + a_7 First_{t-1} + \varepsilon \quad (5)$$

(4) Control variables. We use return on total assets, revenue growth rate, company size, company establishment years, capital structure, the largest shareholding ratio, TobinQ, cash ratio, year, and industry as control variables.

4.2 Data sources

We use samples of A-share listed companies from 2016 to 2020 for empirical research, and samples are selected according to the following criteria: (1) Delete samples of financial industry ; (2) Delete samples of ST companies; (3) Delete samples with missing values, we obtain 15928 observations finally. The data comes from China Stock Market & Accounting Research Database (CSMAR). In order to eliminate the influence of extreme values, we winsorize all continuous variables at 1st and 99th percentile.

4.3 Research model

Hypothesis 1 is tested using formula (6), hypothesis 1 is true if the coefficient of a1 is significantly negative.

$$EDF = a_0 + a_1 AI + Controls + Year + Ind + \varepsilon \quad (6)$$

Hypothesis 2 is tested using formula (7)(8), hypothesis 2 is true if the b3 is significantly positive and the c3 is significantly negative.

$$EDF = b_0 + b_1 AI + b_2 Sub + b_3 AI \times Sub + Controls + Year + Ind + \varepsilon \quad (7)$$

$$EDF = c_0 + c_1 AI + c_2 FC + c_3 AI \times FC + Controls + Year + Ind + \varepsilon \quad (8)$$

Hypothesis 3 is tested using formula (9), if the greater the degree of risk, the greater the negative impact of AI on EDF, then hypothesis 3 is true.

$$EDF = h_0 + h_1 AI + h_2 Risk + h_3 AI \times Risk + Controls + Year + Ind + \varepsilon \quad (9)$$

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Table 1 Variable Definition Table

Variable Nature	Variable Name		Variable Symbol	Variable Calculation
Explained Variable	Financial Distress		*EDF*	Using the KMV model to measure the probability of default, thereby measuring the degree of corporate financial distress
Explanatory Variable	AI Technology Application		*AI*	1 if the company uses AI technology, 0 otherwise
Moderator Variables	Resource Acquisition Ability	Government Subsidy	*Sub*	Government subsidy amount/operating income
		Financial Constraints (FC)	*WW*	*WW* index=0.1292255×*Size*+0.2806241×*CF* +0.0657391×*Growth*+0.5100916×*ISG* － 1.572105×*Lev_ind*+0.4936025×*TLTD* － 0.3375704×*Current*
			KZ	*KZ* index= － 14.21684×*CF* － 7.243019×*CASH* － 5.032141×*DIV*+ 0.4365548×*TobinQ*+3.861434×*Lev*
	Risk Level	Operational Risk	*OR*	Standard deviation of *ROE* in three years
		Financial Risk	*Overlev*	Excessive debt
		Liquidity Risk	*Flex*	Current Assets/Current Liabilities
Control Variables	Return on Total Asset		*ROA*	Net profit/Total assets
	Revenue Growth Rate		*Growth*	Sales revenue growth rate
	The Company Size		*Size*	Natural logarithm of total assets
	Firm Age		*Firmage*	Natural logarithm of the company's age
	Capital Structure		*Lev*	Total Liabilities/Total Assets
	The Largest Shareholding Ratio		*First*	Percent of shares held by the largest shareholder
	TobinQ		*TobinQ*	(Market value of equity+ book value of liabilities) / book value of total assets
	Cash Ratio		*Cash*	(Currency funds + transactional financial assets)/total assets
	Industry		*Ind*	Industry dummy variables
	Year		*Year*	Annual dummy variables

5 Empirical Results

(1) Descriptive statistics

We make annual and industrial statistics on companies using AI, table 2 shows the result. There were only 162 companies using AI technology before the year of 2017, with technological progress and support of national development policy, the number of companies using AI technology is increasing, reaching to 832 by the year of 2020. From an industry perspective shown as table 3, companies using AI technology are mainly concentrated in the manufacturing and information technology industries, and the application of AI technology in other industries is not yet widespread.

Table 2 Annual Statistics of Companies Using AI Technology

2013	2014	2015	2016	2017	2018	2019	2020
21	34	63	162	409	528	656	832

Table 3 Industrial Statistics of Companies Using AI Technology

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Industry name	Number	Total number in industries	Percent	Industry name	Number	Total number in industries	Percent
Manufacturing	432	2,648	16.31%	Education	6	11	54.55%
Information Transmission, Software and Information Technology Services	251	334	75.15%	Production and Supply of Electricity, Heat, Gas and Water	5	115	4.35%
Finance	35	121	28.93%	Water Conservancy, Environment and Public Facilities Management	4	79	5.06%
Scientific Research and Technical Service	17	62	27.42%	Health and Social Work	4	11	36.36%
Transportation, Warehousing and Postal Services	16	108	14.81%	Mining	3	73	4.11%
Wholesale and Retail Trade	14	171	8.19%	Comprehensive	2	11	18.18%
Leasing and Business Services	13	62	20.97%	Agriculture, Forestry, Animal Husbandry and Fishery	1	42	2.38%
Real Estate	11	121	9.09%	Accommodation and Catering	0	10	0.00%
Construction	10	98	10.20%	Residential Services, Repairs and other Services	0	1	0.00%
Culture, Sports and Entertainment	8	54	14.81%				

We make descriptive statistics on the samples. As can be seen in Table 4, the average corporate default risk is 0.19, which means the default risk is not too high. The average application of AI technology is 0.14, shows that AI technology is not widely used. The government subsidy is less generous, the average value is 0, the maximum value is 0.09; the financial constraints are acceptable, the average WW index is 2.17, the KZ index is -5.29; the average operating risk is -0.02, the average financial risk is 0, and the average liquidity risk is 2.34, all at a relative low level. In the other financial data, the companies' ROA is about 0.03, the growth rate is about 17%, the natural logarithm of the asset is about 22.34, the natural logarithm of the companies' age is about 3.01 years, and the asset-liability ratio is about 42%, somewhat high, the proportion of the largest shareholder is about 33%, TobinQ is about 2.40, and ratio of cash to total assets is about 8%.

Table 4 Descriptive Statistics

Variables	*N*	*Mean*	*Sd*	*Min*	*Median*	*Max*
DDKMV	15928	0.19	0.28	0.00	0.07	1.00
AI	15928	0.14	0.35	0.00	0.00	1.00
Sub	15928	0.00	0.01	0.00	0.00	0.09
WW	15761	2.17	0.23	1.50	2.16	2.76
KZ	15819	-5.29	8.50	-49.10	-2.58	2.24
OR	14424	-0.02	2.38	-13.05	0.23	10.33
Overlev	15292	0.00	0.15	-0.36	-0.01	0.40
Flex	15928	2.34	2.23	0.29	1.66	17.40
ROA	15928	0.03	0.07	-0.27	0.04	0.21
Growth	15928	0.17	0.43	-0.62	0.10	2.87
Size	15928	22.34	1.32	19.34	22.17	27.06
Firmage	15928	3.01	0.27	1.95	3.04	3.56

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Lev	15928	0.42	0.20	0.05	0.42	0.94
First	15928	0.33	0.14	0.09	0.31	0.75
TobinQ	15928	2.40	1.78	0.54	1.83	11.62
Cash	15928	0.08	0.14	0.00	0.00	0.71

(2) Regression results

①The impact of AI technology on corporate financial distress

Table 5 shows the effect of AI technology on corporate financial distress. The explained variable is the financial distress of the company, the explanatory variable is the application of AI, columns (1) (2) use OLS model, columns (3) (4) use random panel model, and columns (5) (6) use fixed panel model, in addition, the variable of AI is regressed using current and one lag. The conclusion is the similar, AI technology can alleviate the financial distress of enterprises. The application of AI technology can enable enterprises to improve their resource acquisition abilities, obtain more financing, improve their ability to supervise, manage and control risks, and respond to risks in time. In addition, AI technology can reduce the irrational behaviors of decision makers and help enterprises make correct decisions to deal with crises. Using AI technologies such as data mining and automated data analysis, enterprises can rely on evidence in decision-making instead of relying only on subjective judgments. Therefore, the application of AI can reduce default risks, alleviate the financial distress of enterprises, and this effect plays a role in the current or later period of AI application.

Table 5 Effect of AI Technology on Corporate Financial Distress

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Random panel model		Fixed panel model	
	Current	Lag	Current	Lag	Current	Lag
AI	-0.030***	-0.036***	-0.023***	-0.025***	-0.020***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
ROA	-0.184***	-0.162***	-0.177***	-0.147***	-0.254***	-0.219***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growth	0.015***	0.014**	0.008*	0.006	0.006	0.003
	(0.002)	(0.017)	(0.051)	(0.198)	(0.172)	(0.534)
Size	0.048***	0.044***	0.066***	0.061***	0.105***	0.103***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firmage	-0.035***	-0.038***	-0.058***	-0.059***	-0.576***	-0.645***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Lev	0.604***	0.660***	0.465***	0.535***	0.324***	0.386***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First	0.087***	0.091***	0.134***	0.123***	0.228***	0.218***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TobinQ	-0.003**	-0.009***	0.006***	-0.002	0.012***	0.005***
	(0.018)	(0.000)	(0.000)	(0.189)	(0.000)	(0.002)
Cash	0.016	0.052***	-0.037***	-0.009	-0.047***	-0.026**
	(0.320)	(0.002)	(0.000)	(0.374)	(0.000)	(0.016)
Constant	-1.148***	-0.985***	-1.438***	-1.311***	-0.732***	-0.364
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.267)

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Year	Control	Control	Control	Control	Control	Control
Ind	Control	Control	Control	Control	Control	Control
N	15928	13163	15928	13163	15928	13163
R^2	0.476	0.493	0.179	0.189	0.195	0.204
F	104.615***	103.835***			94.244***	94.923***
Chi ^{2} value			2977.534***	2909.858***		

②Mechanism test of AI technology to alleviate corporate financial distress: Resource acquisition ability

Table 6 shows the mechanism effect of AI technology on corporate financial distress from the prospect of resource acquisition ability. The explained variable is the financial distress of the enterprise, and the explanatory variables are AI, resource acquisition ability, and the multiplication of them. We measure the resource acquisition ability using indexes of government subsidies and financial constraints. Columns (1) (2) are listed as government subsidies, Columns (3) (4) are listed as WW index, Columns (5) (6) are listed as KZ index, both the WW index and KZ index are used to measure financial constraints. It can be seen that when the enterprises obtain less government subsidies, face higher financial constraints, then the effect of AI in alleviating financial difficulties is better. At the same time, since AI needs to be used for a period of time to produce an effect, we test the explanatory variables with one lag period, and the conclusion is the same. AI technology can alleviate the problem of information asymmetry between enterprises and external financial institutions, a large amount of transaction data generated by AI can be used as digital assets of enterprises, helping to obtain financing from banks, and AI technology can improve the efficiency of corporate resource allocation, so that enterprises can operate with existing resources fully, improve their innovation capabilities, and help enterprises alleviate financial difficulties.

Table 6 Effect of AI Technology on Corporate Financial Distress under Different Resource Acquisition Abilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Government subsidy		*WW* index		*KZ* index	
	Current	Lag	Current	Lag	Current	Lag
AI	-0.033***	-0.041***	0.239***	0.306***	-0.028***	-0.032***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Sub	0.304	0.528**				
	(0.140)	(0.034)				
AI×Sub	0.929**	1.224***				
	(0.031)	(0.005)				
WW			-0.062*	-0.076**		
			(0.067)	(0.018)		
AI×WW			-0.126***	-0.160***		
			(0.000)	(0.000)		
KZ					0.017***	0.011***
					(0.000)	(0.000)
AI×KZ					-0.006**	-0.006**
					(0.018)	(0.024)
ROA	-0.183***	-0.157***	-0.187***	-0.228***	-0.037	-0.116***

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	(0.000)	(0.000)	(0.000)	(0.000)	(0.276)	(0.001)
Growth	0.016***	0.013**	0.021***	0.016***	0.013**	0.011*
	(0.001)	(0.024)	(0.000)	(0.010)	(0.010)	(0.075)
Size	0.048***	0.045***	0.060***	0.062***	0.053***	0.049***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firmage	-0.034***	-0.037***	-0.032***	-0.010	-0.035***	-0.031***
	(0.002)	(0.002)	(0.004)	(0.439)	(0.002)	(0.008)
Lev	0.604***	0.663***	0.609***	0.664***	0.536***	0.612***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First	0.087***	0.091***	0.079***	0.061**	0.102***	0.097***
	(0.000)	(0.000)	(0.001)	(0.016)	(0.000)	(0.000)
TobinQ	-0.004**	-0.009***	-0.003**	-0.013***	-0.008***	-0.011***
	(0.013)	(0.000)	(0.020)	(0.000)	(0.000)	(0.000)
Cash	0.017	0.054***	0.009	0.038**	0.140***	0.099***
	(0.287)	(0.001)	(0.583)	(0.034)	(0.000)	(0.000)
Constant	-1.156***	-1.070***	-1.264***	-1.354***	-1.235***	-1.176***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	Control	Control	Control	Control	Control	Control
Ind	Control	Control	Control	Control	Control	Control
N	15928	13163	15761	12048	15928	12984
R^2	0.477	0.494	0.477	0.507	0.482	0.501
F	98.576***	98.155***	98.775***	92.049***	101.676***	101.129***

③ Mechanism test of AI technology to alleviate corporate financial distress: Risk response ability

Table 7 shows the mechanism effect of AI technology application on financial distress from the prospect of risk response ability. The explained variable is the financial distress of the enterprise, the explanatory variables are AI, the enterprise risk level, and the multiplication of them, columns (1) (2) are operational risks, columns (3) (4) are financial risks, and columns (5) (6) are liquidity risks. At the same time, the explanatory variables are regressed using the current and one lag period, the conclusions are similar. It can be seen that the greater the risk, the more obvious effect of AI technology on alleviating financial distress. AI technology can assess risks in advance, manage and control risks in the event, collect a large amount of external information, use deep learning, data mining and other technologies to analyze the law of data, find abnormal situations, estimate corporate risks, and can provide intuitive, real-time data analysis, which can help managers make decisions to deal with risks quickly, reduce the possibility of defaults, and alleviate financial distress. The operational risk is more significant in the one lag period, indicating that AI technology may not be able to work immediately, the effect will be better if it is used longer.

Table 7 Effect of AI Technology on Corporate Financial Distress under Different Risk Levels

	(1)	(2)	(3)	(4)	(5)	(6)
	Operational risk		Financial risk		Liquidity Risk	
	Current	Lag	Current	Lag	Current	Lag
AI	-0.033***	-0.040***	-0.033***	-0.040***	-0.050***	-0.059***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OR	0.001	0.001				

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	(0.231)	(0.228)				
AI×OR	-0.001	-0.005**				
	(0.571)	(0.016)				
Overlev			0.048	0.130***		
			(0.160)	(0.000)		
AI×Overlev			-0.213***	-0.248***		
			(0.000)	(0.000)		
Flex					0.024***	0.020***
					(0.000)	(0.000)
AI×Flex					0.008***	0.008***
					(0.001)	(0.000)
ROA	-0.249***	-0.254***	-0.195***	-0.264***	-0.147***	-0.110***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Growth	0.022***	0.021***	0.015***	0.020***	0.020***	0.009
	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)	(0.140)
Size	0.051***	0.051***	0.049***	0.053***	0.048***	0.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firmage	-0.010	0.011	-0.033***	-0.011	-0.034***	-0.033***
	(0.412)	(0.457)	(0.004)	(0.391)	(0.002)	(0.004)
Lev	0.608***	0.659***	0.599***	0.586***	0.774***	0.802***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First	0.061**	0.037	0.084***	0.066***	0.083***	0.085***
	(0.012)	(0.172)	(0.000)	(0.009)	(0.000)	(0.000)
TobinQ	-0.007***	-0.013***	-0.003**	-0.013***	-0.007***	-0.013***
	(0.000)	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)
Cash	0.018	0.043**	0.010	0.049***	-0.042***	-0.001
	(0.304)	(0.025)	(0.565)	(0.008)	(0.008)	(0.944)
Constant	-1.250***	-1.342***	-1.161***	-1.285***	-1.263***	-1.201***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	Control	Control	Control	Control	Control	Control
Ind	Control	Control	Control	Control	Control	Control
N	14424	10964	15292	11930	15928	13163
R^2	0.487	0.510	0.482	0.511	0.498	0.511
F	93.012***	86.620***	100.466***	94.254***	109.894***	105.549***

(3) Heterogeneity test

① The effect of AI technology on alleviating financial distress under different supply chain concentrations

AI technology makes it possible to remotely and timely monitor, diagnose, control and optimize supply chains that are geographically widely dispersed. AI technology can shorten the distance between enterprises and reduce information asymmetry problem (Hopkins,2021), therefore, for a more dispersed supplier and customer relationship, AI technology plays a better role. In all aspects of the supply chain, various digital smart devices are playing a role in reducing costs, enhancing flexibility, shortening time to market, and improving productivity, optimizing supply chain effectiveness and efficiency, and improving productivity and competitiveness (Khalifa et al.,2021). At the same time, the amount of data generated by end-to-end supply

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chain management is growing exponentially, and large-scale data can be used for complex decision-making by utilizing machine learning and optimization methods (Mišić & Perakis,2020). In the centralized supplier and customer relationship, enterprises can communicate with a small number of suppliers and customers in depth, even share data, suppliers and customers are more inclined to provide trade credit to enterprises to ease the financial pressure of enterprises, and this advantage can also be achieved in decentralized supplier and customer relationships with the help of AI technologies. Using AI technology, enterprises can build a data sharing platform and share data information in time. The degree of information asymmetry between enterprises can be reduced, and rapid business processing can be realized, which can improve the operational efficiency of enterprises, reduce the default risk, and alleviate financial difficulties.

Table 8 shows the results of heterogeneity test. The explanatory variable is the financial distress of the company, and the explanatory variables are AI technology, supply chain concentration and the multiplication of them. Columns (1)-(3) are listed as the top five supplier/customer concentrations, columns (4)-(6) are listed as the largest supplier/customer concentrations, and column (7) is listed as the average of the top 5 suppliers and customers' concentrations. It can be seen that the more dispersed the suppliers/customers are, the better effect of AI technology in alleviating financial distress, and the effect is more obvious with scattered suppliers than with scattered customers, mainly because suppliers can provide trade credit financing to enterprises, which can offer more direct help to alleviate financial distress.

Table 8 Effect of AI Technology on Corporate Financial Distress under Different Supply Chain Concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Top 5 Supplier/Customer			First Supplier/Customer			supply chain
AI	-0.061***	-0.051***	-0.068***	-0.060***	-0.059***	-0.070***	-0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Supplier_Top5	0.027*		0.023				
	(0.090)		(0.155)				
AI×Supplier_Top5	0.078**		0.066*				
	(0.021)		(0.054)				
Customer_Top5		0.019	0.011				
		(0.220)	(0.504)				
AI×Customer_Top5		0.051	0.036				
		(0.109)	(0.271)				
Supplier_Top1				0.031		0.031	
				(0.219)		(0.218)	
AI×Supplier_Top1				0.119**		0.096*	
				(0.021)		(0.059)	
Customer_Top1					0.011	-0.006	
					(0.688)	(0.830)	
AI×Customer_Top1					0.118**	0.096*	
					(0.025)	(0.065)	
Supplychain							0.000*
							(0.074)
AI×Supplychain							0.001**
							(0.023)

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ROA	-0.160***	-0.162***	-0.162***	-0.159***	-0.173***	-0.163***	-0.156***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growth	0.013**	0.013**	0.013**	0.009	0.010	0.010	0.013**
	(0.028)	(0.025)	(0.025)	(0.181)	(0.140)	(0.140)	(0.034)
Size	0.047***	0.046***	0.047***	0.056***	0.055***	0.056***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Company	-0.039***	-0.035***	-0.039***	-0.036***	-0.035***	-0.036***	-0.034***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)	(0.003)	(0.004)
Lev	0.658***	0.652***	0.651***	0.584***	0.589***	0.581***	0.660***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First	0.094***	0.094***	0.096***	0.106***	0.101***	0.108***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TobinQ	-0.009***	-0.009***	-0.009***	-0.006***	-0.005***	-0.006***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)
Cash	0.047***	0.050***	0.048***	0.068***	0.069***	0.070***	0.050***
	(0.005)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Constant	-1.124***	-1.104***	-1.128***	-1.298***	-1.280***	-1.294***	-1.132***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	Control	Control	Control	Control	Control	Control	Control
Ind	Control	Control	Control	Control	Control	Control	Control
N	12852	12844	12760	8764	8926	8700	12936
R^2	0.498	0.494	0.496	0.514	0.513	0.510	0.496
F	96.899***	93.807***	89.644***	68.718***	71.014***	63.369***	95.917***

② The effect of AI technology on alleviating financial distress under different corporate governance levels

While AI algorithms generate output data based on the input data they receive to make automated decisions, but these algorithms which are described as omnipotent may run to the wrong conclusions. In response to the problem that AI algorithms are overestimated, some scholars have raised sharp criticisms. AI algorithms not only take over the decision-making power of humans, but even replace humans. In fact, intelligence is not a complete replacement of the human brain, the humans need to dominate the machine to carry out intelligent practice, and we should persist in the independent status and control ability of humans. Although AI can improve the efficiency of data processing, the data quality of the company will affect the effectiveness of AI technology. Only the data processed by AI is real, can the conclusions be of reference value (Janssen et al.,2020), so the company's earning quality higher, the effect of AI is better. The use of AI also needs to be based on human decision-making, if corporate governance and AI are divided into two parts, and the managers do not consider the data and suggestions provided by the AI system when making decisions, then AI technology cannot play as well as it should be. Corporate governance and AI should complement each other, and executives should be clear about their responsibilities (Hilb,2020; Lipai et al.,2021). Therefore, the better the corporate governance level, the more effective the AI technology will be. We measure the corporate governance level from four aspects: earning quality, investment efficiency, total factor productivity, and innovation efficiency.

Table 9 shows the result of heterogeneity test. The explanatory variable is the financial distress of the com-

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pany, the explanatory variables are AI technology, corporate governance variables, and the interaction of them, column (1) is earning quality, column (2) is overinvestment level, column (3) is total factor productivity, column (4) is innovation efficiency. It can be seen that when the company's earning quality, investment efficiency, total factor productivity and innovation efficiency is higher, then the effect of AI on alleviating financial distress is better, indicating that good corporate governance level is more conducive to the application of AI technology.

Table 9 Effect of AI Technology on Corporate Financial Distress under Different Corporate Governance Levels

	(1)	(2)	(3)	(4)
AI	-0.029***	-0.044***	0.262***	0.003
	(0.000)	(0.000)	(0.000)	(0.799)
EM	0.060**			
	(0.047)			
AI×EM	0.165***			
	(0.004)			
Overinvest		-0.012		
		(0.753)		
AI×Overinvest		0.267***		
		(0.005)		
TFP			0.006	
			(0.276)	
AI×TFP			-0.043***	
			(0.000)	
Innovation				-0.008***
				(0.000)
AI×Innovation				-0.009**
				(0.046)
ROA	-0.236***	-0.228***	-0.170***	-0.188***
	(0.000)	(0.000)	(0.000)	(0.000)
Growth	0.016***	0.020***	0.016***	0.017***
	(0.002)	(0.000)	(0.002)	(0.001)
Size	0.048***	0.050***	0.048***	0.056***
	(0.000)	(0.000)	(0.000)	(0.000)
Firmage	-0.033***	-0.004	-0.036***	-0.041***
	(0.004)	(0.727)	(0.001)	(0.000)
Lev	0.616***	0.621***	0.592***	0.598***
	(0.000)	(0.000)	(0.000)	(0.000)
First	0.085***	0.061**	0.066***	0.064***
	(0.000)	(0.013)	(0.002)	(0.003)
TobinQ	-0.003**	-0.008***	-0.002	-0.002
	(0.049)	(0.000)	(0.115)	(0.245)
Cash	0.023	0.020	0.009	0.015
	(0.171)	(0.251)	(0.566)	(0.369)

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Constant	-1.143***	-1.272***	-1.177***	-1.299***
	(0.000)	(0.000)	(0.000)	(0.000)
Year	Control	Control	Control	Control
Ind	Control	Control	Control	Control
N	15261	13941	15218	15496
R^2	0.479	0.494	0.486	0.486
F	113.101***	94.083***	101.539***	101.461***

③The effect of AI technology on alleviating financial distress under different property rights

State-owned property right is an important property right in China, and state-owned enterprises are important functional carriers for fulfilling the national mission. With the opening of digital economy era and the support of national policies, state-owned enterprises have been given a new era connotation. To create new advantages in the intelligent transformation, state-owned enterprises must play key roles in strategic leadership. The corporate mission represents the unique value model of the enterprise (Grimes et al.,2019). In order to respond to the challenges of intelligence effectively, state-owned enterprises need to play a forward-looking and leading role in the national mission. China aims to guide state-owned enterprises to support the national strategy by promoting the coordination of digital technology, national mission, and state-owned enterprise reform, fulfilling the national mission with high quality (Qi et al.,2021). The state-owned asset supervision system has evolved from "managing enterprises" to "managing capital", which helps promote intelligent transformation further. State-owned enterprises have the support of national policies and shoulder more social responsibilities. The use of AI technology in state-owned enterprises is supported and supervised more by the state, therefore, the effect of AI will be utilized more fully and the effect of alleviating financial difficulties will be better. Table 10 shows the impact of AI technology on corporate financial distress under different property rights. Columns (1) (2) are group tests, and columns (3) (4) are multiplication tests. It can be seen that the effect of AI technology on alleviating financial distress is better in state-owned enterprises, which is consistent with the expected conclusion.

Table 10 Effect of AI Technology on Corporate Financial Distress under Different Property Rights

	(1)	(2)	(3)	(4)
	Group Test		Multiplication Test	
	State=1	State=0	Current	Lag
AI	-0.057***	-0.018***	-0.019***	-0.024***
	(0.001)	(0.003)	(0.002)	(0.000)
State			0.013	0.019**
			(0.111)	(0.029)
AI×State			-0.047***	-0.056***
			(0.006)	(0.003)
ROA	-0.307***	-0.166***	-0.183***	-0.160***
	(0.004)	(0.000)	(0.000)	(0.000)
Growth	0.034***	0.008	0.015***	0.015**
	(0.002)	(0.156)	(0.002)	(0.012)
Size	0.049***	0.042***	0.048***	0.043***
	(0.000)	(0.000)	(0.000)	(0.000)

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Company	-0.012	-0.038***	-0.036***	-0.041***
	(0.693)	(0.000)	(0.002)	(0.001)
Lev	0.920***	0.447***	0.603***	0.660***
	(0.000)	(0.000)	(0.000)	(0.000)
First	0.040	0.108***	0.081***	0.082***
	(0.422)	(0.000)	(0.000)	(0.001)
TobinQ	-0.015***	-0.003**	-0.003**	-0.009***
	(0.003)	(0.010)	(0.028)	(0.000)
Cash	0.026	0.013	0.020	0.056***
	(0.533)	(0.368)	(0.212)	(0.001)
Constant	-1.367***	-0.915***	-1.143***	-1.038***
	(0.000)	(0.000)	(0.000)	(0.000)
Year	Control	Control	Control	Control
Ind	Control	Control	Control	Control
N	5072	10802	15874	13159
R^2	0.525	0.440	0.477	0.494
F	52.875***	63.237***	99.790***	98.746***

(4) Robustness test

①We use method of PSM 1:3 to match the control variables according to whether artificial intelligence technology is used in the year, the results are shown in the table 11, and the conclusions are consistent with the above.

Table 11 Robustness Test using PSM Matching Method

	(1)	(2)	(3)	(4)	(5)	(6)
AI	-0.035***	-0.040***	0.247***	-0.037***	-0.036***	-0.055***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Sub		0.337				
		(0.245)				
AI×Sub		1.102***				
		(0.009)				
WW			-0.061			
			(0.157)			
AI×WW			-0.131***			
			(0.001)			
OR				0.000		
				(0.879)		
AI×OR				-0.003		
				(0.177)		
Overlev					0.110***	
					(0.009)	
AI×Overlev					-0.180***	
					(0.000)	
Flex						0.016***
						(0.000)

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AI×Flex						0.007***
						(0.000)
Controls &Constant	Control	Control	Control	Control	Control	Control
Year &Ind	Control	Control	Control	Control	Control	Control
N	4663	4663	4299	3978	4219	4663
R^2	0.487	0.488	0.502	0.506	0.505	0.506
F	44.437***	42.243***	41.208***	39.288***	42.887***	46.440***

②We use the DID model to reduce endogenous problems. Table 12 shows the result, the explanatory variable is the financial distress of the company, the explanatory variables are the multiplication term of whether the company adopts the AI technology (Treat) and the dummy variables before and after the adoption of the AI (Time), we control the company's individual effect and time effect, and the conclusions are consistent with above. We also conduct a balanced trend test, and find that AI played a significant role since 2018, which is similar to the actual condition. The number of companies using AI technology in China has rapidly increased since 2018. In addition, we adopt year by year PSM 1:1 matching, and then further expand it to panel data, the results are shown in columns (4)-(6), we can see the conclusions are consistent.

Table 12 Robustness Test using DID Model

	(1)	(2)	(3)	(4)	(5)	(6)
	All the samples			PSM		
Treat×Time	-0.014***	-0.020***		-0.009*	-0.014***	
	(0.003)	(0.000)		(0.082)	(0.005)	
Treat×Year2016			0.004			0.000
			(0.521)			(0.961)
Treat×Year2017			-0.003			-0.004
			(0.704)			(0.636)
Treat×Year2018			-0.036***			-0.021**
			(0.000)			(0.042)
Treat×Year2019			-0.043***			-0.030***
			(0.000)			(0.002)
Treat×Year2020			-0.037***			-0.020**
			(0.000)			(0.029)
Controls		Control	Control		Control	Control
		Control	Control		Control	Control
Constant	0.140***	-0.732***	-1.629***	0.135***	-0.783**	-1.131***
	(0.000)	(0.010)	(0.000)	(0.000)	(0.019)	(0.000)
Year	Control	Control	Control	Control	Control	Control
Fixed effects	Control	Control	Control	Control	Control	Control
N	17142	15928	18352	10107	10107	11610
R^2	0.090	0.195	0.202	0.076	0.172	0.418
F	158.724***	94.244***	104.889***	81.676***	50.918***	110.064***

③We replace the measurement method of AI variable. When the words of "artificial intelligence" appear twice or more in the annual reports, the variable of AI is defined as 1. When the words of "artificial intelli-

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gence" do not appear, AI is defined as 0, and the rest are missing values. We use this variable for regression, and the conclusions remain unchanged.

④We extend the sample time from 2015 to 2020, and the conclusions of the empirical tests remain unchanged.

6. Conclusion and Discussion

We study the effect and mechanism of AI technology on corporate financial distress, and use the data of Chinese listed companies to conduct empirical tests, find the following conclusions:

Firstly, AI technology can alleviate the financial distress of enterprises. AI technology can reduce information asymmetry with external stakeholders, help enterprises obtain more external resources, and AI technology can enable enterprises to manage company risks better, give early warnings before risks come, and take measures quickly when facing with risks. At the same time, AI technology provides references for managers' decision-making through data analysis, reduces managers' irrational behaviors, and helps make correct decisions in times of crisis, thereby reducing the corporate financial distress.

Secondly, when the degree of corporate financial constraints is greater and the government subsidies are less, the effect of AI technology on alleviating financial difficulties is more obvious, indicating that AI technology can alleviate financial difficulties by improving companies' resource acquisition abilities. AI technology can help enterprises obtain more external resources, and a large number of transactions generated by AI can be used as digital assets, helping enterprises to improve their abilities to lend from banks and increase credit levels. In addition, AI technology can improve the efficiency of resource allocation, improve the innovation ability and work efficiency, and allocate resources to the greatest extent to help enterprises tide over difficult times, reduce default risks, and alleviate financial difficulties.

Thirdly, the higher the operational risk, financial risk, and liquidity risk of the enterprise, the more obvious the effect of AI technology on alleviating financial distress, indicating that AI technology can alleviate financial distress through increasing enterprises' risk response abilities. Enterprises can use data mining, deep learning, network search and other methods to improve their risk response abilities, and use visual charts to detect and warn risks in time. Measures can also be taken in time to reduce corporate financial distress when risks come.

Fourthly, the heterogeneity tests found that when suppliers/customers are more dispersed, and the corporate governance environment is better, as well as the nature is state-owned property rights, then AI technology is more effective in reducing financial distress. AI technology can shorten the spatial distance between companies in supply chain, enterprises can also share data and risks in the decentralized supply chain relationship by building a supply chain ecosystem. In the decentralized supply chain relationship, AI can play a higher role. In addition, AI needs people to make decisions using analyzed data, and the data based on AI also should to be true and reliable to reach appropriate conclusions. Therefore, in the governance environment with better earning quality, investment efficiency, total factor productivity and innovation efficiency, AI technology plays a better role. State-owned enterprises undertake the responsibilities of national development, play an exem-

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plary role in the use of AI technology, and are also supervised by the state strictly. Therefore, AI technology plays a better role in state-owned enterprises.

We put forward the following suggestions: Firstly, enterprises should adapt to the development of technology, increase investment in AI, and apply AI technology as soon as possible, because AI technology can improve the ability of enterprises to obtain resources and respond to risks, and alleviate the financial difficulties. Especially in the current environment with repeated epidemics and instable international relationship, the application of AI technology can improve the abilities of enterprises to respond to crises and help them get through difficult times. Secondly, the use of AI also requires human decision-making and support, enterprises must improve the information accuracy, only by ensuring the quality of input data, valuable analysis conclusions can be drawn from AI technology. At the same time, AI technology and managers' decision-making should complement with each other, not be independent, and AI system should not be separated from human control. Managers' decision-making should refer to the suggestions of AI system, so as to formulate corresponding countermeasures and suggestions, and help the company make right decisions. Thirdly, as an important industrial pillar of the country, state-owned enterprises have the support of state finance, expert advice, and strict supervision by the State-owned Assets Supervision and Administration Commission. More efforts should be made to strengthen the research, development, use and supervision of AI, so as to give full play to the effects of AI and provide a demonstration for other enterprises to apply AI technology better.

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