The Impact of Intelligent Transformation on Financial Risk of Manufacturing Firms:

Based on Financing Constraint Mediation Tests

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Abstract. This paper takes a total of 2, 532 data from 1, 125 listed manufacturing companies in A-share from 2015 to 2022 as samples and uses stata17.0 multiple linear regression and neural network model SVM to verify the negative impact of intelligent transformation on the financial risk of manufacturing enterprises. Measurement method by selecting six indicators using the entropy weighting method to construct the intelligent comprehensive index system, selecting the Altman-Z value to measure the enterprise financial risk and adopting the assignment method to carry out the subsequent empirical evidence, and taking the financing constraints as the mediating variable to measure the impact of intelligent transformation on the financial risk of manufacturing enterprises. Based on the basic regression test, it is obtained that intelligent transformation can reduce enterprise financial risk; based on the mediator test, it is found that intelligent transformation of manufacturing enterprises reduces enterprise financial risk by alleviating financing constraints; based on the test of enterprise heterogeneity, it is found that intelligent transformation of state-owned enterprises can reduce enterprise financial risk more effectively compared with non-state-owned enterprises. The use of the neural network model SVM further confirms the robustness of the conclusion that the intelligent transformation of manufacturing enterprises can effectively reduce corporate financial risk, which is of strong guiding significance for enterprise development.

Keywords: Intelligent transformation; Corporate financial risk; Financing constraints; Neural network model

1 INTRODUCTION

In the background of the new round of information technology to countries to bring a huge impact, the intelligent transformation of manufacturing enterprises has been widely concerned, but also become the main direction of the country's current. 2022 September 9, "The New Era of Industry and Information Technology Development" conference.

R. Magdalena et al. (eds.), *Proceedings of the 2024 9th International Conference on Social Sciences and Economic Development (ICSSED 2024)*, Advances in Economics, Business and Management Research 289,
https://doi.org/10.2991/978-94-6463-459-4_88

China's industrial and information technology management department also made clear the importance of the digitalization, networking, and intelligence of China's manufacturing industry to promote the efficient growth of China's manufacturing industry and cultivate innovative growth points in the national economy. As the representative of China's manufacturing intelligence, modern manufacturing networks and intelligent manufacturing have been transformed into a new important reference standard for China's market economic development and social progress. As China's progress in the integration of dualization is getting faster and faster, the strength of enterprises in the manufacturing industry in the application of information technology and automation is also continuing to strengthen. The intelligent process of manufacturing enterprises has not only helped them reinvent themselves in all aspects of R&D, production, and marketing but has also used tools such as big data and Internet platforms to provide users with a more accurate and personalized portrait to efficiently meet their individual needs. This not only significantly improves the operational management efficiency of enterprises, but also reduces the deviation between financial performance and expected operational goals, which has a profound impact on the financial risks of manufacturing enterprises.

The current research on the impact of intelligent transformation on enterprise behavior mainly focuses on the fact that intelligent transformation has an impact on enterprise investment efficiency, enterprise total factor productivity, and enterprise performance. For example, Zeng Lingling and Xiao Yannan (2022)[1] selected 105 listed companies as intelligent manufacturing pilot companies as the research sample, and confirmed that the degree of intelligence has an obvious positive impact on improving the investment efficiency of enterprises. Xie Yanxiang et al. (2023)[2] pointed out that the application of industrial robots can improve the total factor productivity of enterprises through the effects of innovation, technology, and scale, and Zhang Wanli et al. (2022)[3]suggested that the role of intelligence on the total factor productivity of enterprises shows a "U" type development trend. Li Wanhong and Wang Fan (2022)[4] chose traditional manufacturing enterprises listed in Shanghai and Shenzhen A-share companies from 2011 to 2019 as the research object and confirmed that intelligent transformation could improve the performance of traditional manufacturing enterprises by reducing the cost stickiness. The research literature mentioned above mainly focuses on the perspective of enterprise value and explores the positive effects of intelligent transformation of enterprises, but the financial risk, which is opposite to enterprise value, seems to have not been paid enough attention. At the current stage, in order to promote sustainable development, it has become a key strategy to prevent financial risks and improve the development level of enterprises. Considering this, the intelligent transformation of manufacturing enterprises is an inevitable result of technological progress, so from a microscopic point of view, what kind of impact will it have on the financial risk of manufacturing enterprises?

From a micro perspective, this study quantifies the specific impact of manufacturing firms' intelligence on their financial risk using cross-sectional data of A-share manufacturing companies listed in Shanghai and Shenzhen from 2015 to 2022. On this basis, financing constraints are also introduced as a mediating variable, and the heterogeneity of manufacturing firms is explored in depth. The potential academic value of this study focuses on two major aspects: (1) The study introduces the comprehensive assessment index dimension of manufacturing enterprise intelligence and new patent application indexes based on the traditional literature. (2) This study utilizes a neural network model to quantitatively study the impact of intelligent transformation of manufacturing enterprises on enterprise financial risk and analyzes the differences in different enterprises.

2 LITERATURE REVIEW AND THEORETICAL ANALYSIS

2.1 Literature review

Impact of Intelligent Transformation

Intelligent transformation refers to the use of advanced intelligent technologies by an enterprise to induce significant changes in organizational processes in research and development, production, and marketing, thereby optimizing the overall operational processes of the enterprise (VIAL et al., 2019)[5]. Current research suggests that the intelligent transformation of a firm will bring about significant changes to its resources, capabilities, strategies, and financial position. More specifically, (1) through the intelligent transformation of enterprises, the requirements of enterprises for reserve talents will also change significantly, requiring higher skills, better overall quality, and eliminating the need for inefficient repetitive labor, which will help to optimize the labor structure within the enterprise (Zhang Yuan and Li Huanjie, 2022)[6]; (2) the intelligent transformation will have a positive impact on the productivity of the enterprise, reducing production costs by increasing capital investment and creating new jobs in the context of intelligence, which will help to improve the productivity of enterprises (Acemoglu et al., 2019)[7]; (3) Intelligent transformation will drive enterprises to adjust their business strategies in order to build a "differentiated + service-oriented " competitive environment (Qi Yudong and Xu Kaige, 2022)[8]; (4) Intelligent transformation helps to enhance the performance of enterprises in financial aspects, such as improving the financial status of enterprises as well as improving the overall performance of enterprises (Li Wanhong and Wang Fan, 2022)4.

Intelligent Transformation and Corporate Financial Risk.

Xiang Dewei (1994)[9] proposed that the financial risk of the enterprise reflects the business risk of the enterprise at the micro level, which is mainly reflected in the financial performance and financial position, mainly covering four major types of risks, such as fundraising, investment, capital flow, and income distribution. The current research on intelligent transformation and enterprise risk mainly focuses on: information technology, Internet technology and digital transformation can reduce enterprise financial risk, for example, Feng Su ling and Zhao Shu (2021)[10]The progress of information technology helps to alleviate the enterprise's limitations in financing, and the financing constraints and financial risk show a non-linear interrelationship. With strong regulatory constraints, its inhibitory effect on corporate financial risk is more significant.

An Su xia et al. (2022)[11] argued that Internet information technology has significant advantages in data processing and information transmission, which is able to identify and assess risks in complex environments, and through the integration with traditional industries, realize the "Internet +" model to reduce the financial risk of enterprises. Li, Jingming and Golden City (2023)[12] suggested that digital transformation has a negative impact on corporate financial risk.

nowadays, there are fewer studies on intelligent transformation and enterprise financial risk, mainly focusing on financialization, digital economy and digital finance can reduce enterprise financial risk through financial aspects. At present, both domestic and foreign countries are oriented to the new direction of intelligent transformation of manufacturing enterprises, as a common financial risk of enterprises, whether manufacturing enterprises can be reduced through intelligent transformation to promote the better development of enterprises has practical significance.

2.2 Theoretical analysis and research hypothesis

Intelligent transformation of traditional manufacturing enterprises refers to the use of a new generation of information technology and advanced manufacturing technology, such as big data, Internet technology, and artificial intelligence technology, by upgrading the manufacturing equipment and manufacturing process to achieve real-time dynamic sensing, interaction, and execution, to realize the product lifecycle intelligence of design, production, marketing, and service. Its core idea is to integrate the latest information technology, artificial intelligence, and other cutting-edge technologies into the operation and management of enterprises, to achieve instant management and optimization of the entire life cycle of products. Manufacturing enterprises utilize big data, cloud computing, and internet platform technology to simplify the process of production and transaction, thus improving the efficiency of production and operation, and reducing the cost and expense of the enterprise. At the same time, companies relying on intelligent risk control strategies can accurately collect and efficiently assess their financial status, thereby significantly reducing the credit risks that may be associated with the traditional financial system. With the support of artificial intelligence and blockchain technology, enterprises can process a large amount of data at a lower cost, dig deeper into the credit information of enterprises, improve the truthfulness, accuracy, and circulation of information and data, and reduce the information occlusion of enterprises to the market (Gomber et al., 2018)[13]. Most enterprises generally face the problem of financing difficulties and high costs, but through intelligent transformation, the problem of financing constraints of enterprises has been effectively alleviated, and the risk of debt default has also been reduced. Promoting the in-depth transformation of manufacturing enterprises in the direction of intelligence can not only narrow the gap of business capabilities between enterprises and optimize the ecological environment of the market, but also help to enhance information exchange and help enterprises get rid of the obstacles to their development, thus reducing financial risks, enhancing economic returns, and ensuring their sustainable development. On this basis, hypothesis H1 is proposed.

H1: Intelligent transformation of manufacturing enterprises can effectively reduce corporate financial risk.

The financial risk of an enterprise is closely linked to all its capital flows, of which financing constraints are a key aspect. The intelligent transformation of the manufacturing industry has provided enterprises with more financing avenues, making corporate disclosure more comprehensive and transparent. This highly transparent corporate information enhances the confidence of market investors, which attracts a large inflow of external capital (Li Jingming, and Huang Jincheng, 2023)[12]. Further, when the financing constraints of enterprises change, it will have a direct impact on their financial risks. If intelligent transformation makes the financing constraints of manufacturing enterprises appropriately mitigated, and the capital flow of enterprises becomes more reasonable and sufficient, then it will positively promote the production and operation activities of the enterprises, thus increasing the revenue, improving the performance, and reducing the financial risk. Based on the above analysis, we can regard the above process of intelligent transformation to alleviate financing constraints and thus reduce enterprise financial risk as a coherent and interactive whole. Therefore, in the face of financing difficulties, if enterprises choose intelligent transformation without considering the shortage of capital, they may suffer from stagnation of production and operation, and at the same time, the financial risk of enterprises may also increase. Based on this, hypothesis H2 is proposed.

H2: Intelligent transformation of manufacturing firms acts on corporate financial risk by affecting financing constraints and thus corporate financial risk.

3 RESEARCH DESIGN

3.1 Data sources

In this study, manufacturing companies listed on A-shares in Shanghai and Shenzhen from 2015 to 2022 are selected as the research object. The sample data were obtained from the Cathay Pacific database, and the following operations were carried out to ensure the accuracy of the data: the samples with severely missing variable data were removed, and the data of suspended companies were removed. To exclude the influence of unfavorable factors, this study has shrunk all continuous variables in the range of 1% before and after. The above data screening resulted in 2532 sample observations.

3.2 Definition of variables

Explained Variables

The explanatory variable is corporate financial risk (Zscore). Indicators of corporate financial risk are commonly used nowadays, such as the Z_score proposed by Altman (1968) [14] and the Logistic model bankruptcy prediction index established by Ohlson (1980)[15], the Z_score model is mainly a multivariate evaluation model constructed from five aspects of the financial indicators by weighting, Altman-Z value to measure the key explanatory variable of corporate financial risk.

Altman-Z itself means that the lower the value, the higher the financial risk of the enterprise. According to the scoring criteria of the "Z-Score" model, when "Z⩽1.61", the company's financial condition is unstable and on the verge of bankruptcy, are assigned a value of 2; when "Z⩾2.99", the company's overall financial condition is relatively healthy, are assigned a value of 0; when "1.61<Z<2.99", the company's financial condition is relatively healthy, are assigned a value of 1.

Core explanatory variables

Integrated Indicator of Manufacturing Intelligence (IM). This paper selects indicators from six measurement indicators: the number of patent applications、 patent applications, R&D investment、the ratio of R&D investment to operating income、the number of R&D personnel in the manufacturing industry、 the ratio of the number of R&D personnel to the total number of employees. The above contains a total of which together build a comprehensive index of manufacturing intelligence. Based on the constructed evaluation index system, the entropy weight method is used to quantify the degree of intelligence of manufacturing enterprises. The entropy weighting method determines the weights of the indicators according to the dispersed characteristics of the data of each indicator, which can avoid the influence of subjective factors in the process of empowerment, and thus can more objectively and accurately measure the degree of intelligence of manufacturing enterprises. The specific implementation steps of the entropy weight method will not be repeated.

This paper through the 2015-2022 A-share manufacturing industry intelligence comprehensive index to measure, after the normalization of the indicators, the manufacturing industry intelligence comprehensive index of each weight value as Table 1. The value of the manufacturing enterprise intelligence index obtained between 0 and 1, the larger, indicating that the higher the manufacturing enterprise intelligence, and vice versa, indicating that the level of intelligence of the manufacturing enterprise the lower.

Table 1. Manufacturing Intelligence Comprehensive Indicator Weights

Variable	unit	weights
the number of patent applications	pcs	0.092
the number of R&D personnel/the total number of employees	%	0.209
patent applications	%	0.140
the number of R&D personnel	person	0.176
R&D investment	RMB	0.166
the ratio of R&D investment to operating income	%	0.217

Mediating variables

Mediating variable financing constraint (SA). Financing constraints can cause enterprises to be unable to carry out a series of production and operation activities due to financial reasons, there are various indicators to measure the financing constraints of enterprises, concerning HADLOCK C J and PIERCE J R et al. (2010)[16], the SA index is chosen as an assessment criterion for the financing constraints, compared with the other indexes, the SA index only considers the size and age of the firm, which can avoid the endogeneity problem like the KZ index may cause. Given that the SA index may present a negative value, we choose the SA index as an absolute value, and a larger SA value means that firms face more serious financing constraints.

Control variables

In this paper, financial level variables as well as corporate governance variables are selected. The financial level variables are: cash flow (cfo), profitability (roa), growth, and financial leverage (lev); and the corporate governance variables are: firm size, age at listing, board size, shareholding concentration (first), shareholding checks and balances (balance), dual office (dua), and property rights (soe). nature (soe). We also control for year-fixed effects, thus controlling for the effects of individual and time factors.

3.3 Model construction

Basic regression model construction

To verify the impact of intelligent transformation of the manufacturing industry on enterprise financial risk, this paper constructs the following basic regression model.

$$\mathrm{Zscore}_{i,t} = \beta_0 + \beta_1 \mathrm{IM} + \sum \mathrm{CT} + \sum \mathrm{Y} + \sum \mathrm{In} + \varepsilon_{i,t} \tag{1}$$

where CT represents the control variable, In denotes industry fixed effects, Y denotes time fixed effects, ε i, t is the random error term, and the lower footnotes i and t denote individuals and years, respectively:

If the coefficient of the manufacturing intelligent transformation index is significantly less than zero, then this means that promoting manufacturing intelligence helps to significantly reduce the financial risk of enterprises, thus proving that H1 is valid; if the coefficient of the manufacturing intelligent transformation index is significantly greater than zero, this means that promoting manufacturing intelligence helps to significantly reduce the financial risk of enterprises, thus proving that H1 is not valid.

Intermediary mechanisms

Based on the presuppositions of previous studies, the intelligent transformation of the manufacturing industry helps to reduce the financing pressure of enterprises, which further reduces the financial risk of enterprises. This paper draws on the stepwise regression to test the mechanism of the role of intelligent transformation of the manufacturing industry on enterprise financial risk in a step-by-step manner through the intermediary variable of financing constraints, to construct the model (2)~ (3)

$$\mathrm{Sa}_{i,t} = \delta_0 + \delta_1 \mathrm{IM} + \sum \mathrm{CT} + \sum \mathrm{Y} + \sum \mathrm{In} + \varepsilon_{i,t} \tag{2}$$

$$\mathrm{Zscore}_{i,t} = \mu_0 + \mu_1 \mathrm{IM} + \mu_2 \mathrm{Sa}_{i,t} + \sum \mathrm{CT} + \sum \mathrm{Y} + \sum \mathrm{In} + \varepsilon_{i,t} \tag{3}$$

In models (2)~ (3), the main attention should be paid to coefficients 1 and 2. If coefficient 1 in equation (2) is significantly negative, it means that the intelligent transformation of manufacturing enterprises can effectively alleviate the enterprise's financing constraints; at the same time, if coefficients 1 and 2 in equation (3) are significantly negative, it indicates that the intelligent transformation of manufacturing enterprises can reduce the enterprise's financial risk through the channel of alleviating the financing constraints, i.e., the financing constraints play an intermediate role, and H2 is verified. If the coefficient 1 in equation (2) is not negative or one of 1 and 2 is not negative, then it indicates that the intelligent transformation of manufacturing enterprises can not effectively alleviate the financing constraints of enterprises; the intelligent transformation of manufacturing enterprises can not reduce the enterprise financial risk through the channel of alleviating the financing constraints, and H2 is not valid.

4 EMPIRICAL ANALYSIS

4.1 Correlation analysis

In the matrix of correlation coefficients of variables obtained using stata17.0, some correlation coefficients are shown in Table 2, which shows that the correlation coefficient between corporate financial risk (Zscore) and intelligent transformation (IM) is -0.115***. This means that at the 1% level, there is a significant negative correlation between the intelligent transformation of manufacturing companies and corporate financial risk, indicating that the intelligent transformation of the manufacturing industry can significantly reduce the financial risk of the enterprise. The H1 hypothesis has been preliminarily verified. It can also be observed that the correlation coefficient between intelligent transformation (IM) and financing constraints (SA) is -0.224***, which indicates that the intelligent transformation of manufacturing enterprises and financing constraints are significantly negatively correlated at the 1% level, and the H2 hypothesis has been partially verified.

Table 2. Correlation coefficients for selected variables

Variable	Zscore	IM	SA	roa	lev	growth
Zscore	1					
IM	-0.115***	1				
SA	0.044**	-0.224***	1			
roa	-0.365***	0.0290	-0.047**	1		
lev	0.604***	-0.167***	0.126***	-0.375***	1	
growth	-0.097***	0.164***	-0.180***	0.202***	-0.184***	1

Note: Data from csmar database Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ the same as below

To test whether there is a multicollinearity problem between the variables, this paper uses VIF to empirically test, and the results can be found that the VIF value of each variable is near 2, a much smaller than the required <10, which indicates that the influence of multicollinearity between the variables is small, and it can be further empirically demonstrated by model regression.

4.2 Basic regression results

In this study, based on the basic regression model, Stata17.0 software multiple linear regression analysis was used to verify the specific impact of manufacturing enterprises on financial risk in the process of intelligent transformation, and the analysis results are shown in Table 3.

The results in column (1) show that the regression coefficient of intelligent transformation (IM) reaches -1.728 and shows a significant negative correlation at the 1% level; column (2) results in a regression coefficient of -0.760, and the addition of control variables causes the regression coefficient to decrease, but still shows a significant negative correlation at the 1% level; column (3) after conducting year fixed effects mixed with industry fixed effects, the relative to column (2) the results are relatively slightly improved. Comprehensive column (1) (2) (3) results can be seen, it is found that there is a significant negative effect between the financial risk of enterprises and the intelligent transformation of listed companies, which means that the intelligent transformation of the manufacturing industry can significantly reduce the financial risk of enterprises, so the hypothesis H1 is valid.

Table 3. Basic regression results

Variable	(1) Zscore	(2) Zscore	(3) Zscore
IM	-1.728^{***}	-0.760^{***}	-0.799^{***}
	(0.296)	(0.246)	(0.261)
CT	No	Yes	Yes
N	2532.000	2532.000	2532.000
F	34.054	146.605	82.894
r2	0.013	0.411	0.421
r2_a	0.013	0.408	0.416
industry	No	No	Yes
year	No	No	Yes

4.3 Intermediation mechanism test

The specific regression results of the mediation mechanism are shown in columns (1)-(2) of Table 4. As can be seen from column (1) of Table 4, the regression coefficient of IM is -1.301***, which is significantly negative at a 1% probability level, indicating that intelligent transformation of manufacturing enterprises can alleviate corporate financing constraints. The coefficients of IM and SA in Column (2) are -1.000*** and -0.155***, both significant at 1% level, which indicates that intelligent transformation of manufacturing enterprises is conducive to alleviating the financing constraints and endows enterprises with more financial vitality; both coefficients are significantly negative at 1% level, which also indicates that financing constraints are also embodied in the impact of the intelligent transformation of enterprises on corporate financial risk. the mediating role, the H2 hypothesis is established.

Table 4. Intermediation mechanism regression results

Variable	(1) SA	(2) Zscore
IM	-1.301***	-1.000***
	(0.144)	(0.264)
SA	-	-0.155***
	-	(0.036)
CT	Yes	Yes
N	2532.000	2532.000
F	48.958	80.643
r2	0.300	0.425
r2_a	0.294	0.420
In	Yes	Yes
Y	Yes	Yes

4.4 Heterogeneity test

The underlying regression analysis in Table 3 in the previous section explores the potential impact of manufacturing enterprises' transformation to intelligence on their financial risks only from the perspective of the overall sample size. However, state-owned and non-state-owned enterprises in the manufacturing industry show some differences in terms of intelligent transformation and reduction of corporate financial risk due to differences like property rights. In the test results in Table 5, the heterogeneity test is based on the regression analysis of the nature of enterprises. Both types of enterprises undergoing intelligent transformation can significantly reduce their financial risks. Specifically, for every one-unit increase in intelligent transformation, the financial risk of non-state-owned firms decreases by -0.625 units, while the financial risk of state-owned firms decreases by -2.033 units. This intelligent transformation produces a more significant negative impact in reducing the financial risk of state-owned enterprises, further confirming that hypothesis H1 is valid.

4.5 Robustness Tests

(1) Replacement variable method. This study uses the redefinition of the explanatory variables to test their robustness, corporate financial leverage (lev) as a substitute variable for corporate financial risk, and the model was re-regression analyzed, the results of which are shown in Table 5. From the data table, it can be observed that by using

corporate financial leverage (lev) as a proxy for corporate financial risk in the regression analysis, the results were obtained as follows: the regression coefficient of IM is -0.952***, still significantly negative at 1% probability level, the results of the regression analysis are highly consistent with the results of the underlying regression analysis, which proves that the conclusions of this study are robust.

(2) One-period lag test. To solve the endogeneity problem that may arise between variables, this study uses the data of the enterprise financial risk variable lagged one period, and re-conducts the regression analysis of the basic regression model that previously constructed the role of intelligent transformation of manufacturing enterprises on financial risk. The test results are shown in the last column of the test results in Table 5, and the regression coefficient of intelligent transformation (IM) in the lagged one period shows a significant negative correlation at the 10% level, which suggests that the above conclusions are robust and that the role of intelligent transformation of manufacturing enterprises on financial risk has a certain degree of jaggedness.

Table 5. Test results

Variable	Heterogeneity test		Robustness Tests	
	(non-state-owned)	(state-owned)	(Replacement Zscore)	(One-period lag)
	Zscore	Zscore	lev	Zscore
IM	-0.625**	-2.033***	-0.952***	-0.695*
	(0.261)	(0.623)	(0.103)	(0.396)
CT	Yes	Yes	Yes	Yes
N	1856.000	676.000	2532.000	1233.000
F	43.523	29.258	97.447	35.401
r2	0.353	0.508	0.472	0.402
r2_a	0.345	0.491	0.467	0.391
In	Yes	Yes	Yes	Yes
Y	Yes	Yes	Yes	Yes

5 FURTHER ANALYSIS

5.1 Complex Neural Network Models

Further, to quantitatively study how the intelligent transformation of the manufacturing industry affects corporate financial risk and the role of financing constraints (SA) in this process, this paper constructs the following machine learning neural network model SVM to explore the impact of correlation at a finer granularity, and the core formula of the SVM model is as follows:

$$\min_{W,b,\xi} \frac{1}{2}||W||^2 + C\sum_{i=1}^{n}\xi_i \quad s.t.\, y_i\,(X_i^T W + b) \geq 1 - \xi_i \qquad \xi_i \geq 0, i = 1,2,\ldots n \tag{4}$$

model SVM (4), focusing on the MLP neural network model parameters, because the dummy variables can not accurately quantitatively go to measure the enterprise financial risk, so in the use of neural network model training, the original value of the enterprise financial risk is Altman-Z. In this paper, we will train the neural network model according to the sample data, a more fine-grained portrayal of the manufacturing industry's intelligent transformation, the financing constraints of the corporate financial risk of the influence, and show and analyze the laws in the form of graphical representation.

5.2 Analysis of neural network model

Using the Python machine learning codebase sklearn an attempt is made to model corporate financial risk using the classical SVM model (Support Vector Machine, also known as Support Vector Network), a supervised learning model with associated learning algorithms commonly used in regression analysis of data. At the same time with the help of kernel trick (kernel trick) and soft interval maximization, you can learn a nonlinear SVM that can fit more complex data scenarios.

This time all the sample data were used for training to fit the data distribution. After several rounds of re-learning, the model was finally converged. For easy viewing, the results of model learning were displayed in a 3D scene using the python drawing learning library tool Seaborn. The results of the model learned from the model are displayed as Fig.1:

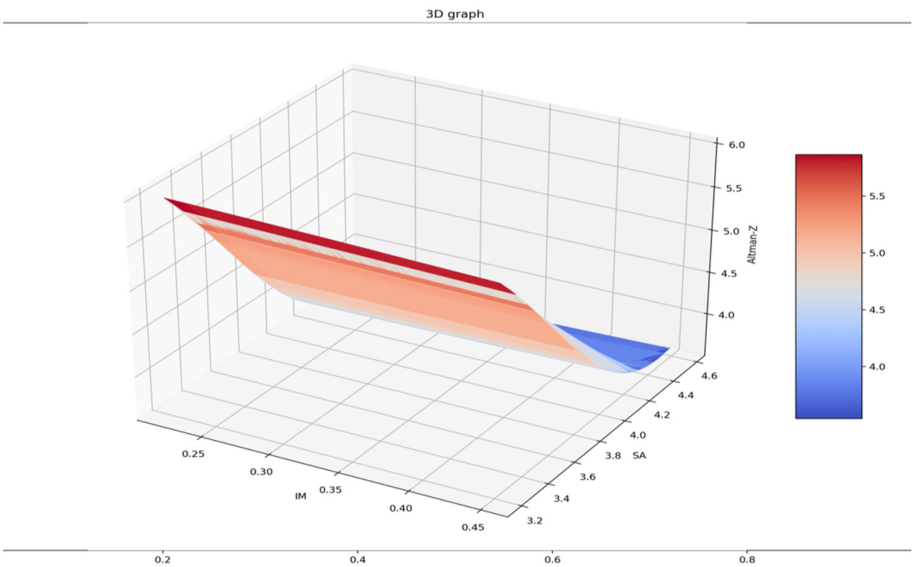

Fig. 1. Display of model learning results

Through the neural network modeling results, the following conclusions can be found:

(1) Financing constraints have a strong mediating effect on corporate financial risk. When the financing constraint is larger (greater than 4.3), the degree of intelligent transformation of the enterprise has less impact on the enterprise's financial risk, and the financial risk is controlled; when the financing constraint is smaller (less than 4.0), the higher the degree of intelligent transformation of the enterprise, the lower the financial risk of the enterprise, and the trend is obvious.

(2) The data also verifies the robustness of the conclusion that the intelligent transformation of the manufacturing industry can effectively reduce enterprise financial risk.

6 CONCLUSIONS AND IMPLICATIONS

This study explores the impact of intelligent transformation on enterprise financial risk based on the opportunity of combining intelligence with manufacturing enterprises. The results of the study show that: the intelligent transformation of manufacturing enterprises can effectively reduce the financial risk of enterprises, and this conclusion is robust; the transformation of manufacturing enterprises to intelligence can effectively reduce the financing pressure of enterprises to a certain extent, thus further reducing the risk of enterprise finance Further research found that, in the financing constraints are small, the intelligent transformation of the financial risk is more significant; from the aspect of ownership From the perspective of ownership, the intelligent transformation of state-owned enterprises can more effectively reduce the financial risk of enterprises compared with non-state-owned enterprises.

According to the above conclusions, the following insights are obtained: for manufacturing enterprises, the use of the state vigorously promotes the development of intelligent transformation to seize the favorable opportunity for transformation, take the lead in establishing the core advantages of market development, closely follow the development trend of intelligence, and promote the intelligent reform of the enterprise, which is the key to realize the stable and upward development of the enterprise. In addition, enterprises need to further strengthen the use of information technology, transform the traditional production model, and take advantage of emerging information technology to solve the problem of information asymmetry that exists in enterprises. Enterprises should make full use of the various development opportunities brought about by intelligent transformation, make full use of the economic and other policy support given by the national government to enterprises in intelligent transformation, and adopt intelligent differentiated development according to their actual situation, to improve their financial situation.

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