

Research on the Impact of Artificial Intelligence on the Resilience of the Manufacturing Industry Chain

Meng Fu

School of Economics, Harbin University of Commerce, Harbin 150028, Heilongjiang, China

Corresponding author: Meng Fu (e-mail: gracefuhappy@163.com)

ABSTRACT Under increasing geopolitical uncertainty, black-swan and gray-rhino events have accelerated the structural reshaping of global manufacturing industry chains, making industrial-chain resilience a key condition for stable economic operation. Existing studies mainly focus on artificial intelligence applications in single manufacturing processes, while the mechanism through which artificial intelligence affects manufacturing industry-chain resilience remains insufficiently clarified. Taking China's manufacturing industry chain as the research object, this paper analyzes the theoretical relationship between artificial intelligence and industrial-chain resilience, identifies current resilience challenges, and conducts empirical testing based on panel data from 30 Chinese provinces from 2012 to 2023. The entropy weight method is used to measure manufacturing industry-chain resilience, while a double fixed-effects model and mediation-effect model are applied to examine direct effects, transmission paths, and regional heterogeneity. The results show that artificial intelligence significantly enhances the resilience of the manufacturing industry chain, and the conclusion remains robust after robustness checks. Mechanism analysis indicates that technological innovation and digital empowerment are the main transmission channels. Heterogeneity analysis shows stronger enabling effects in eastern regions and areas with advanced digital-economy development.

INDEX TERMS artificial intelligence, manufacturing industry chain, industrial resilience, double fixed effects model, digital empowerment

I. INTRODUCTION

IN the face of profound changes in the global economic environment and accelerated technological innovation and industrial transformation, manufacturing industry chain's stability and risk resistance have gradually become the key indicators to measure the industrial competitiveness of a country. The report of the 20th National Congress of the Communist Party of China proposed the goal of "strengthening the resilience and security of industrial and supply chains" [1]. It is very clear that the high-quality development of China's manufacturing industry aims at further improving the overall level of the manufacturing industry chain. At present, China's manufacturing industry has established a complete industrial system. However, the problems such as bottlenecks in core technologies, dependence on single links in the manufacturing industry chain and delays in risk early warning still exist. In addition, the external environment of the manufacturing industry chain is also facing new challenges. On the one hand, global trade frictions and geopolitical conflicts have caused frequent disruptions and blockages in the industrial chain. On the other hand, as a strategic technology that drives the new technological revo-

lution, artificial intelligence characterized by deep learning, autonomous decision-making and collaborative connectivity provides a new solution to the problem of insufficient resilience of the manufacturing industry chain. Therefore, it has important theoretical and practical significance to study the impact of artificial intelligence on the resilience of the manufacturing industry chain [2,3]. Taking the whole manufacturing industry chain in China as the research object, this study aims at exploring the mechanism, heterogeneity and optimization path by which artificial intelligence affects the resilience of industry chain, so as to provide empirical basis and reference for improving the resilience of China's manufacturing industry chain.

The main contributions of this paper are as follows: First, from the perspective of research, this paper breaks through the research practice of single link and puts artificial intelligence and manufacturing industry chain resilience into the same analytical framework for the first time to conduct an in-depth study on their intrinsic connection, which enriches the related research of digital technology and industry chain resilience. Second, from the methodological perspective, this paper adopts the combined method of

entropy weight method, double fixed-effects model and mediation effect model to improve the empirical research and solve the problem of single-method research. Third, from the practical perspective, this paper explores the path and heterogeneous effect of artificial intelligence in empowering the resilience of industrial chain, and provides targeted suggestions for improving the optimization of AI application and enhancing the resilience of industrial chain in different regions and types of manufacturing enterprises. The rest of this paper is arranged as follows: Section 2 analyzes the current challenges faced by the resilience of the manufacturing industry chain; Section 3 explains the research method and data source; Section 4 explains and analyzes the empirical results; Section 5 concludes the study, discusses the limitations and prospects for further research [4].

II. PROBLEMS AND CHALLENGES

The primary issue facing the resilience of the manufacturing industry chain is the lack of independent and controllable capabilities in core links, highlighting the fragility of the industry chain. In the field of high-end manufacturing, the core technologies of China's high-end chips, aviation engines, high-end CNC machine tools and other core products are still dominated by foreign enterprises. The import dependence of key raw materials and components is high, and the import dependence of some strategic resources far exceeds the safety threshold. Once subjected to external shocks such as export controls and geopolitical conflicts, it is easy to cause the interruption of the industrial chain. At the same time, the traditional manufacturing industry chain has long followed the development model of "efficiency first", with centralized layout and single links, forming a "single point dependence" pattern. The coordination between upstream and downstream enterprises is insufficient, and the homogenization of industrial clusters is severe. In the face of market fluctuations, capacity adjustments, or sudden crises, it is difficult to quickly achieve capacity switching and resource allocation, and the ability to resist risks is weak. In addition, the problem of information asymmetry in various links of the industrial chain is prominent, and the phenomenon of data silos is widespread, resulting in poor connection between production, circulation, sales and other links, further exacerbating the vulnerability of the industrial chain.

In the process of empowering the resilience of the manufacturing industry chain with artificial intelligence, there are also multiple challenges at the levels of technology, talent, and ecology. On the technical level, the integration depth between artificial intelligence and manufacturing is insufficient, and most manufacturing enterprises are still stuck in the shallow application of artificial intelligence technology, lacking independent research and development capabilities for core algorithms and intelligent hardware. High end intelligent devices rely on imports, and insufficient technological adaptability leads to a significant reduction

in empowerment effects. At the talent level, there is a shortage of compound talents who not only master artificial intelligence technology but also are familiar with manufacturing processes, which has become an important bottleneck restricting the deep integration of the two. Some small and medium-sized enterprises find it difficult to promote the implementation of artificial intelligence applications due to talent shortages. At the ecological level, the construction of digital infrastructure is uneven, and the digital infrastructure in the central and western regions is weak, making it difficult to support the widespread application of artificial intelligence technology; At the same time, the standard system and laws and regulations for artificial intelligence applications are not yet sound, and data security and privacy protection issues are prominent, further constraining the empowering effect of artificial intelligence on the resilience of the industrial chain [5,6].

III. METHOD

A. ENTROPY WEIGHT METHOD

This article uses the entropy weight method to construct an evaluation index system for the resilience of the manufacturing industry chain, which is used to quantify the resilience level of the manufacturing industry chain in 30 provinces in China. This method can objectively reflect the importance of each evaluation indicator, effectively avoid the bias caused by subjective weighting, and provide scientifically reliable explained variable data for subsequent empirical analysis.

In specific operations, the four core dimensions of resistance, resilience, adaptability, and innovation are first selected, and 12 specific evaluation indicators are screened to comprehensively cover key links in the operation of the industry chain. The collected raw data is standardized and divided into positive and negative indicators based on their properties. Corresponding standardization formulas are used to eliminate the impact of dimensional differences in different indicators and ensure comparability of the data.

Then, the information entropy and weight of each indicator are calculated (the smaller the information entropy, the higher the distinguishability of the indicator and the corresponding weight). The calculated entropy weight values of the 12 indicators are shown in Table A1. Finally, through weighted summation, the comprehensive score of manufacturing industry chain resilience for each province and year is obtained, laying a data foundation for subsequent research.

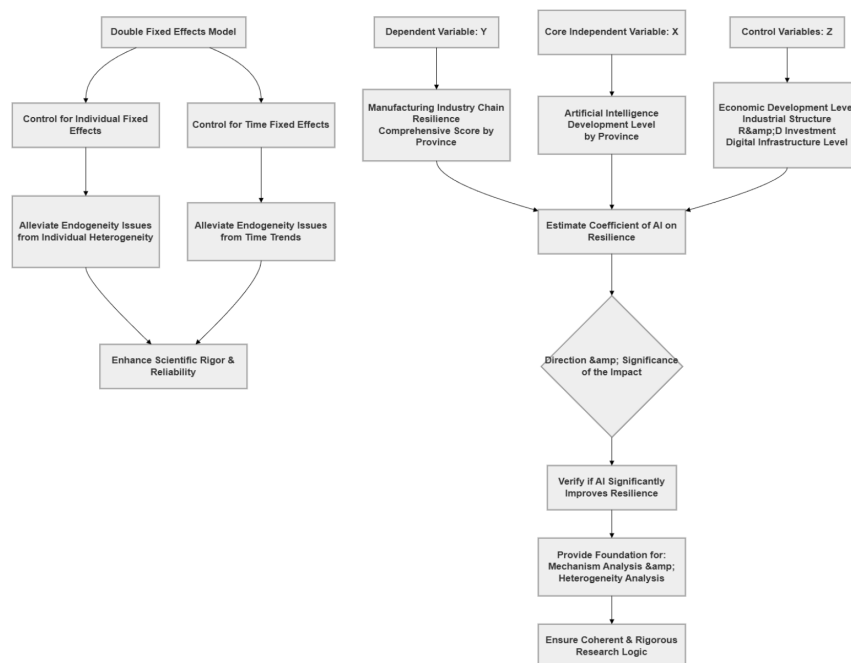
B. DOUBLE FIXED EFFECTS MODEL

In order to explore the direct impact of artificial intelligence on the resilience of manufacturing industry chain (as shown in Fig.1), this study establishes the double fixed-effects model for empirical testing [7,8]. This model can control for individual fixed effects and time fixed effects effectively, solve endogeneity problems caused by individual heterogeneity and time trends, and improve the scientificity and robustness of the research results. In this study, the

TABLE 1. A1 Entropy Weights of 12 Indicators for Manufacturing Industry Chain Resilience

Dimension	Indicator Name	Information Entropy	Weight Value
Resistance	Industrial chain concentration	0.862	0.089
Resistance	Import dependence of key components	0.835	0.102
Resistance	Capacity utilization rate	0.891	0.076
Resilience	Emergency response speed	0.847	0.097
Resilience	Supply chain recovery cycle	0.829	0.105
Resilience	Resource allocation efficiency	0.883	0.080
Adaptability	Market demand response capability	0.876	0.083
Adaptability	Cross-regional collaboration capacity	0.897	0.073
Adaptability	Diversification of supply sources	0.854	0.094
Innovation	Core technology R&D investment intensity	0.792	0.121
Innovation	Number of effective invention patents	0.806	0.115
Innovation	New product sales revenue ratio	0.905	0.069
Total	—	—	1.000

Note: Weights are normalized to sum to 1. Higher weight indicates greater contribution to manufacturing industry chain resilience.

**FIGURE 1.** Double fixed effects model

dependent variable is the comprehensive index of provincial manufacturing industry chain resilience calculated by the entropy weight method.

The core independent variable is the provincial artificial intelligence development level, measured by a composite index constructed from three dimensions:

- (1) number of artificial intelligence enterprises;
- (2) number of granted AI invention patents;
- (3) amount of AI-related fixed-asset investment.

The index is standardized and weighted to reflect the

comprehensive AI development level of each province.

At the same time, control variables are included. These control variables cover the regional level of economic development, industrial structure, R&D input, digital infrastructure capacity, industrial chain concentration, etc., to better explain the influencing factors of industry chain resilience. By establishing this model, we can accurately estimate the size of the impact coefficient of artificial intelligence on the resilience of the manufacturing industry chain, explore the specific direction and statistical significance of the impact,

and verify whether artificial intelligence has a significant enhancing effect on the resilience of the manufacturing industry chain. This empirical basis ensures the rigor and reliability of the mechanism analysis and heterogeneity analysis later in this chapter [9,10].

C. MEDIATION EFFECT MODEL

To probe into the intrinsic mechanism by which artificial intelligence exerts influence on the resilience of industrial chain of manufacturing industry (as depicted in Figure 2), this study advances technological innovation and digital empowerment as the mediating variables and constructs a mediation effect model for empirical testing. The test of mediation effects follows a three-step analytical procedure.

The first step is to test the total effect of artificial intelligence on industrial chain resilience, that is, to verify the direct effect of artificial intelligence by adopting the double fixed-effects model established in the previous section. The second step is to test the effect of artificial intelligence on the two mediating variables, that is, to examine the correlation between artificial intelligence and technological innovation as well as digital empowerment and verify the statistical significance of the correlation. The third step puts artificial intelligence and the two mediating variables into the model simultaneously, and then examines the effect of the two mediating variables on the resilience of industrial chain. The significant coefficient of mediating variable and the reduction in the absolute value of the coefficient of artificial intelligence compared with the first step test indicate the mediating effect. By means of the model, we can make it clear that the effects of artificial intelligence on the resilience of industrial chain are respectively manifested through technological innovation effects and digital empowerment effects. This deepens the rigor and specificity of the research findings and provides a more solid theoretical basis for subsequent practical recommendations.

IV. RESULTS AND DISCUSSION

A. BENCHMARK REGRESSION RESULTS AND ANALYSIS

Regression coefficients of the benchmark regression are presented in Table 1. The regression coefficient of the artificial intelligence development level (measured by AI enterprises, patents, and investment) is 0.324, significant at the 1% level ($t = 5.78$), indicating that the advancement of artificial intelligence exerts a significant positive driving effect on the resilience of manufacturing industry chain. That is, the comprehensive resilience score of manufacturing industry chain increases 0.324 points when the artificial intelligence development level increases by one unit, which is consistent with the theoretical expectations of this study.

To present the benchmark regression results more intuitively, the empirical data and regression coefficients are presented in the subsequent table. Individual and time fixed effects are controlled. R^2 adj. is used to evaluate the good-

ness of fit of the model, and F -statistic = 38.62 ($p < 0.001$) indicates that the overall significance of the model is valid.

From Table 2, the R^2 value of the adjusted R^2 is 0.682, indicating that the goodness of fit of the model is strong, and the model can explain 68.2% of the variance of manufacturing industry chain resilience. In addition, the regression coefficients of control variables, including regional economic development, R&D investment, and digital infrastructure, are all positive, and statistically significant, which means that when regional economic development is promoted, more R&D investment is made, and digital infrastructure is strengthened, the industrial chain resilience will be improved. At the same time, the regression coefficient of industrial chain concentration is negative and significant, and the regression coefficient of industrial chain concentration is negative and significant. That is, an industrial chain with too concentrated a structure will reduce the risk resistance of the industrial chain and make the problem of insufficient resilience worse. Therefore, these results further prove that artificial intelligence, as an important part of digital technology, can effectively improve the operational efficiency of industrial chains, enhance the ability to resist risks, and lay the foundation for the subsequent mechanism analysis and heterogeneity analysis.

B. RESULTS AND ANALYSIS OF MEDIATION EFFECT TEST

Results of test of mediation effect show that technological innovation and digital empowerment have partial effects of mediating effect. In the second step, as shown in Table 5, the total effect of artificial intelligence on industrial chain resilience in the first step is significantly positive, with the regression coefficient being

0.324. Second, the regression coefficients of artificial intelligence on technological innovation and digital empowerment are 0.286 and 0.301 respectively, and both are significantly positive at the 1% level, meaning that artificial intelligence can significantly promote technological innovation and digital empowerment. In the third step, when technological innovation and digital empowerment are introduced into the model, the regression coefficients of technological innovation and digital empowerment are 0.215 and 0.198 respectively, and both are significantly positive. The regression coefficient of artificial intelligence decreases to 0.187 (still significantly positive), which indicates that artificial intelligence not only significantly promotes industrial chain resilience from the direct effect, but also significantly promotes industrial chain resilience from the indirect effect of promoting technological innovation and enhancing digital empowerment. Technological innovation enhances the independent control level of the industrial chain by solving key technological bottlenecks and optimizing product structure; digital empowerment promotes industrial chain resilience by breaking through data islands, enhancing collaborative efficiency and finely dividing industrial chain resources. Together, they constitute the key link through which artificial

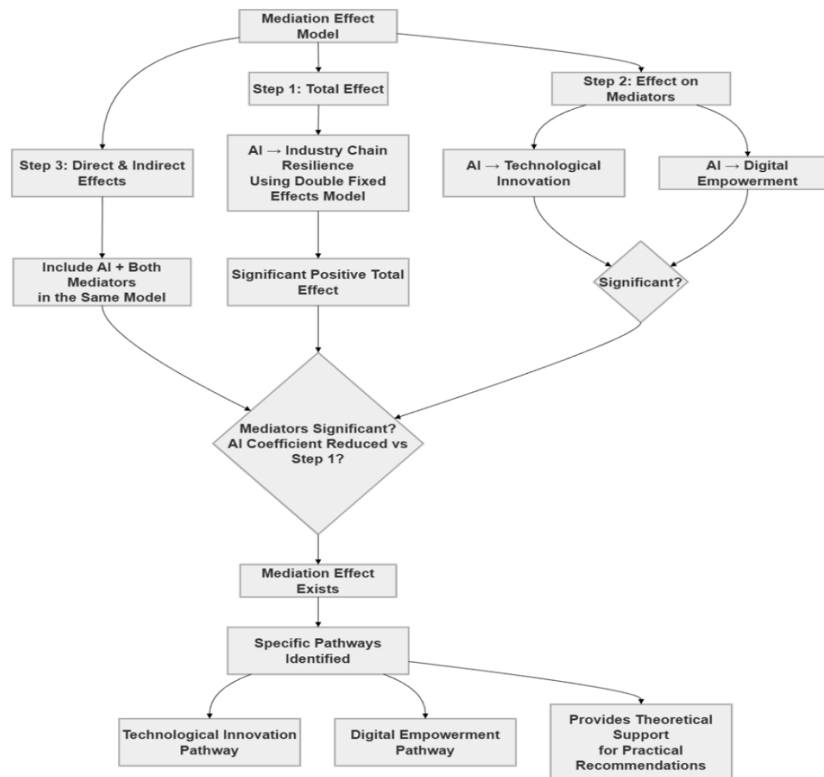


FIGURE 2. Mediation effect model

TABLE 2. Benchmark regression results

Variable	Coefficient	Standard error	T-value	P-value
Development level of artificial intelligence	0.324***	0.056	5.78	0.000
Regional economic development level	0.217***	0.042	5.17	0.000
Industrial structure	0.103**	0.041	2.51	0.012
R&D investment	0.289***	0.053	5.45	0.000
Digital infrastructure level	0.196***	0.048	4.08	0.000
Concentration of industrial chain	-0.152***	0.039	-3.89	0.000
Constant term	1.235***	0.214	5.77	0.000
Individual fixed effects	Y	-	-	-
Fixed time effect	Y	-	-	-
N	360	-	-	-
Adjust R ²	0.682	-	-	-
F value	38.62	-	-	0.000

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels; N=360 is the sample size (30 provinces x 12 years);

intelligence empowers industrial chain resilience.

C. HETEROGENEITY ANALYSIS RESULTS AND DISCUSSION

Heterogeneity analysis based on regional disparities and digital economy development level analysis show that artificial intelligence empowerment on manufacturing industry

chain resilience presents significant heterogeneity. In terms of region, the regression coefficient of artificial intelligence on industrial chain resilience in the eastern region is 0.412, which is much larger than that in the central region (0.258) and western region (0.236). This is because the digital infrastructure in the eastern region is more complete, there is more R&D investment, and interdisciplinary talents are

more aggregated, making the artificial intelligence and manufacturing integration degree deeper, and the empowerment effect stronger. While, the central and western regions have not played the empowering effect of artificial intelligence due to the insufficient digital infrastructure and few talents. From the perspective of digital economy development level, the empowerment coefficient of high digital economy level (0.389) is significantly larger than that of low digital economy level (0.207). In general, a robust digital economy creates a good ecological environment for artificial intelligence empowerment: a higher level of digital economy promotes more intensive integration between artificial intelligence and manufacturing industry, and then industrial chain resilience is strengthened more effectively. Furthermore robustness test such as replacing dependent variable and removing outlier are conducted and the core conclusions are still consistent, which verifies the high reliability of study conclusion.

V. CONCLUSION

This paper investigates the influence of artificial intelligence on the resilience of manufacturing industry chain. In response to the problems of correlation mechanism, transmission pathway and heterogeneous characteristics between artificial intelligence and resilience of manufacturing industry chain, the research findings show that artificial intelligence has a significantly positive impact on the resilience of manufacturing industry chain. Such effect is partly through technological innovation and digital empowerment. Meanwhile, the empowering effect of artificial intelligence shows heterogeneous characteristics in different regions and levels of development of digital economy, and the effect in eastern region and regions with more developed digital economy is stronger. The theoretical contribution of this paper is to extend the related researches on digital technology and industrial chain resilience, and to construct the analytical frame and methodological system for the study of effect of artificial intelligence on industrial chain resilience. Practically, the paper puts forward the corresponding policy recommendations to improve resilience of manufacturing industry chain in China: increasing investment in R&D of core artificial intelligence technology, promoting the integrated development of artificial intelligence and manufacturing, upgrading construction of digital base, cultivating interdisciplinary talents, and designing region-specific differentiated strategies. This study has some limitations: only provincial-level panel data are used, and there is no analysis at industry level or enterprise level. In the future, the analysis scope can be further improved and researches can be conducted on the heterogeneous empowering effect of artificial intelligence in different manufacturing industries and enterprises of different scales, so as to provide more targeted support for improving industrial chain resilience in a precise way.

AUTHOR CONTRIBUTIONS

Meng Fu designed, collected and analyzed the data, and drafted the manuscript. Meng Fu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Meng Fu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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