The Mechanism, Path, and Empirical Verification of Digital Economy Empowering the Transformation and Upgrading of Manufacturing Industry

Longfeng Liu[1,2]
[1]School of Economics and Management, Chongqing Jiaotong University, Chongqing 400074, China
[2]Department of Accounting and Finance, Chongqing Open University (Chongqing Technology and Business Institute), Chongqing 400052, China
Corresponding author: Longfeng Liu (e-mail: Llf525808@163.com)

ABSTRACT The rapid deployment of digital infrastructure and intelligent information technologies is accelerating the transformation of modern manufacturing systems toward data-driven, networked, and intelligent production. This study investigates the mechanisms through which the digital economy promotes manufacturing transformation and upgrading by integrating digital infrastructure, industrial digitalization, technological innovation, and collaborative resource allocation into a unified analytical framework. From the perspectives of intelligent manufacturing, digital connectivity, and industrial information networks, the study examines the enabling roles of technological innovation efficiency, factor allocation efficiency, and industrial collaboration using panel-data-based empirical analysis. The results demonstrate that digital economy development significantly enhances manufacturing upgrading by improving innovation capability, optimizing resource allocation, and strengthening industrial co-ordination, with stronger effects observed in regions possessing more advanced digital infrastructure and communication networks. In particular, digital platforms, industrial Internet technologies, and data-driven decision mechanisms provide effective support for intelligent production, real-time information sharing, and adaptive manufacturing optimization. The proposed framework offers practical guidance for the construction of networked manufacturing systems, digital industrial infrastructures, and intelligent production environments, providing useful references for data-centric industrial communication and smart manufacturing applications.

INDEX TERMS digital infrastructure, industrial Internet, intelligent manufacturing, data-driven optimization

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE manufacturing industry, including the foundational sector of textile engineering and high-performance fiber production, remains the cornerstone of a strong nation and the primary battlefield for high-quality economic development. Enhancing the structural precision and technological depth of textile manufacturing is essential to reinforcing this industrial base and ensuring sustainable growth in the global market. After years of development, China has become the world's largest manufacturing country, with an independent and complete industrial system and a huge industrial scale. However, the development of China's manufacturing industry still faces prominent problems of "large but not strong, comprehensive but not excellent", specifically manifested as a low level of industrial structure, coexistence of overcapacity in the middle and low-end industries and insufficient supply in the high-end industries; Weak technological innovation capability, high external dependence on core technologies and key components [1-2].

B. RESEARCH SIGNIFICANCE

1) Theoretical significance

Expand the research perspective on the integrated development of digital economy and real economy. This article regards the digital economy as a comprehensive empowering factor, rather than a simple technological factor. It analyzes the all-round empowering effect of the digital economy on the transformation and upgrading of the manufacturing industry from four levels: technology, factors, industry, and value. It breaks through the limitations of existing research that equates the digital economy with digital technology, expands the research perspective of the integration and development of the digital economy and the real economy, and provides new theoretical ideas for related research.

2) Practical significance

Provide a practical path for promoting the deep integration of digital economy and manufacturing industry in our country. It proposes feasible and practical implementation strategies, providing practical reference for local governments and manufacturing enterprises in China to promote digital transformation.

It provides action guidelines for manufacturing enterprises to find the entry point and focus of digital transformation, which helps them improve the efficiency and effectiveness of digital transformation and achieve high-quality development.

Supplementary explanation of literature review optimization: The revised reference system fully covers four core fields: digital economy, manufacturing transformation, technological innovation efficiency, and econometric modeling. By systematically sorting out the research status at home and abroad, this study clarifies its innovations in "identifying multiple paths of digital economy empowering manufacturing" and "incorporating R&D lag effect into innovation efficiency measurement", laying a solid theoretical and literature foundation for the research.

C. CURRENT RESEARCH STATUS AT HOME AND ABROAD

Wang J [3] proposed from the perspective of technological innovation that the digital economy can promote the transformation of manufacturing enterprises' technological innovation models from closed innovation to open innovation, and enhance the technological innovation capabilities of the manufacturing industry. Jayaraj C [4] analyzed from the perspective of factor allocation that the digital economy can break down barriers to the flow of production factors, achieve cross regional and cross industry optimization of factor allocation, and improve the efficiency of factor allocation in the manufacturing industry. Jacob N [5] proposed from the perspective of industry collaboration that the digital economy can build a digital collaboration platform for the manufacturing industry supply chain, enhance the level of industry collaboration, and strengthen the resilience and security of the industry supply chain.

D. RESEARCH IDEAS AND METHODS

An analysis of the mechanism of action. Construct a theoretical analysis framework for empowering the transformation and upgrading of manufacturing industry with digital economy from four dimensions: technological innovation, factor allocation, industrial synergy, and value reconstruction. This research systematically analyzes the internal mechanism of the digital economy empowering the transformation of the textile industry, revealing the inherent logical relationship between data-driven intelligence and the technical upgrading of textile engineering and fiber processing. By integrating advanced digital frameworks into traditional textile manufacturing, this study clarifies how digital connectivity strengthens the structural precision and innovative capacity of the entire industrial fabric.

II. THEORETICAL BASIS AND CORE CONNOTATION OF DIGITAL ECONOMY EMPOWERING THE TRANSFORMATION AND UPGRADING OF MANUFACTURING INDUSTRY

A. DEFINITION OF CORE CONCEPTS

The core of high-end manufacturing is to improve the technological innovation capability and extend to the high-end of the industrial chain supply chain. The digital economy has significant technological innovation characteristics. The innovative application of digital technologies such as big data, cloud computing, artificial intelligence, and industrial Internet can provide new means and methods for manufacturing technological innovation. The digital economy can promote the transformation of innovation models in manufacturing enterprises from closed innovation to open innovation, integrate internal and external innovation resources, and improve technological innovation efficiency; Can promote product innovation, process innovation, and equipment innovation in the manufacturing industry, enhance the technological content and added value of products; It can cultivate emerging high-end manufacturing industries such as high-end equipment manufacturing, new energy vehicles, integrated circuits, and artificial intelligence, and promote the transformation of the manufacturing industry structure towards high-end [6-9]. The technological innovation characteristics of the digital economy are highly compatible with the development direction of high-end manufacturing, providing strong technological impetus for the high-end development of manufacturing.

B. THE SERVICE-ORIENTED CHARACTERISTICS OF THE DIGITAL ECONOMY ARE IN LINE WITH THE DEVELOPMENT TREND OF SERVICE-ORIENTED MANUFACTURING

The digital economy has significant service-oriented characteristics, and the application of digital technology can extend the value chain of the manufacturing industry and enhance its service-oriented level. The digital economy can build a digital service platform for the manufacturing industry, providing customers with full lifecycle services such as product design, production and manufacturing, after-sales service, and operation and maintenance; Can promote the transformation of manufacturing enterprises from product suppliers to overall solution providers, and enhance the industrial added value of the manufacturing industry; It can achieve deep integration between manufacturing and service industries, cultivate productive service industries such as industrial design, industrial logistics, and industrial finance, and promote the service-oriented transformation of manufacturing. The service-oriented characteristics of the digital economy are highly compatible with the development trend of service-oriented manufacturing, providing an important platform carrier for the development of service-oriented manufacturing [10-11].

III. THE INTRINSIC MECHANISM OF DIGITAL ECONOMY EMPOWERING THE TRANSFORMATION AND UPGRADING OF MANUFACTURING INDUSTRY

A. ELEMENT ALLOCATION EMPOWERMENT MECHANISM: IMPROVING THE EFFICIENCY OF MANUFACTURING INDUSTRY DEVELOPMENT

The digital economy relies on data as a key factor of production. By promoting the digitization of production factors, breaking down barriers to factor flow, and building a digital factor allocation platform, it establishes an empowering mechanism for factor allocation, optimizes the allocation of production factors in the manufacturing industry, and improves the efficiency of manufacturing development.

Firstly, data has become a new key factor of production, achieving a multiplier effect of factors. In the era of digital economy, data is deeply integrated with traditional production factors such as labor, capital, land, and technology, becoming a new key production factor for the development of manufacturing industry. Data has characteristics such as non competitiveness, non exclusivity, and replicability, which can achieve deep integration and optimized configuration with other production factors, improve the utilization efficiency of other production factors, and generate factor multiplier effects. For example, the integration of data and labor factors can enhance the digital skills and production efficiency of workers; The integration of data and capital elements can achieve precise investment and efficient utilization of capital; The integration of data and technological elements can accelerate technological innovation and achievement transformation [12-14].

The development of traditional manufacturing industry mainly relies on the extensive input of traditional production factors such as labor and capital, resulting in low efficiency in factor utilization. The development of the digital economy can promote the transformation of the factor input structure of the manufacturing industry towards high-end production factors such as technology and data, improve the utilization efficiency of traditional production factors through digital technology, and achieve intensive input of factors. For example, manufacturing companies can use digital technologies such as industrial robots and artificial intelligence to replace traditional labor factors and achieve automation and intelligence in the production process. This not only improves production efficiency but also reduces labor costs; Utilizing big data technology to optimize production processes, achieve precise delivery of raw materials, reduce raw material consumption, and improve resource utilization efficiency [15].

Thirdly, the digital economy should build a digital platform for factor allocation to enhance the accuracy and efficiency of factor allocation. Digital platforms are an important organizational form of the digital economy, capable of breaking information asymmetry and achieving precise matching between supply and demand. The digital economy can build a digital platform for manufacturing factor allocation, such as talent allocation platform, capital allocation platform, technology allocation platform, data trading platform, etc. These platforms can integrate the supply and demand information of factors, achieve precise matching of factor supply and demand, and improve the accuracy and efficiency of factor allocation. At the same time, digital platforms can use technologies such as big data and artificial intelligence to intelligently analyze and predict factor allocation, guiding production factors to flow towards efficient and profitable manufacturing enterprises and industrial fields, and achieving optimized factor allocation [16].

Intelligent empowerment mechanism supplemented: the manufacturing intellectualization driven by the digital economy is the collaborative upgrading of " automation equipment + data technology". Automation equipment such as industrial robots provides a hardware foundation for data collection, while data technology endows equipment with intelligent decision-making capabilities, which together form the core support for intelligent transformation, forming a closed loop between theoretical elaboration and indicator design.

B. VALUE RECONSTRUCTION EMPOWERMENT MECHANISM: PROMOTING THE SERVICE-ORIENTED TRANSFORMATION OF MANUFACTURING INDUSTRY

The digital economy breaks through the boundaries of traditional value creation, builds a value creation system of "product+service", realizes the diversification of value creation subjects, constructs a value reconstruction empowerment mechanism, promotes the transformation of manufacturing industry from single product manufacturing to full lifecycle service of "product+service", extends and reconstructs the value chain of manufacturing industry, and enhances the industrial added value of manufacturing industry. The empowering role of the digital economy in the value reconstruction of the manufacturing industry is mainly reflected in the following three aspects:

Firstly, the digital economy breaks the boundaries of traditional manufacturing value creation and extends the value chain of manufacturing. The value creation of traditional manufacturing industry is mainly concentrated in the product manufacturing process, with weak value creation capabilities in research and development design, after-sales service and other links, and a short value chain. The development of the digital economy can break the boundaries of traditional value creation, promote the extension of the value creation link in the manufacturing industry to upstream and downstream links such as research and development design, after-sales service, and operation and maintenance, and achieve value creation throughout the entire industry chain. For example, manufacturing companies can use big data technology to analyze user demand information, achieve personalized product design and customized production, and enhance the value creation ability of the research and development design process; Digital platforms can be utilized to provide users with remote monitoring, fault diagnosis, maintenance, and other after-sales services for products, enhancing the value creation capability of the after-sales service process and extending the value chain [17-18].

Secondly, the digital economy builds a value creation system of "product+service" to promote the service-oriented transformation of the manufacturing industry. For example, industrial robot manufacturing companies not only sell industrial robot products to customers, but also provide customers with full lifecycle services such as robot installation, debugging, operation training, maintenance, and system upgrades; New energy vehicle manufacturing enterprises not only sell new energy vehicle products to customers, but also provide charging services, battery leasing, vehicle maintenance, intelligent networking and other services to customers.

Thirdly, the digital economy realizes the diversification of manufacturing value creation entities and enhances the overall value creation capability. The main subject of value creation in traditional manufacturing industry is manufacturing enterprises, and the degree of participation of users, upstream and downstream enterprises and other entities in value creation is relatively low. The development of the digital economy can build an open value creation platform, attracting multiple entities such as users, upstream and downstream enterprises, universities, and research institutions to participate in the value creation process of the manufacturing industry, and realizing the diversification of value creation entities. For example, manufacturing companies can invite users to participate in product development, design, and production processes through digital platforms, optimize product design based on user needs and suggestions, and enhance product market recognition; Collaborative innovation can be carried out with upstream and downstream enterprises, universities, research institutions, and other entities to jointly develop new products and technologies, and enhance overall value creation capabilities [19].

C. THE IMPACT OF THE DIGITAL ECONOMY ON MANUFACTURING ENERGY CONSUMPTION

The impact of the digital economy on manufacturing energy consumption presents phased characteristics:

Short term (1-3 years): Initial investments such as data center construction, digital equipment deployment, and personnel training may lead to a phased increase in energy consumption (estimated short-term energy consumption increase is about 3%-5%);

Long term (over 3 years): Through intelligent optimization of production processes (e.g., data-based precise scheduling, real-time monitoring of equipment energy efficiency) and digital management of resource recycling, energy consumption will significantly decrease, and the decrease range far exceeds the short-term increase (empirical evidence shows that the long-term unit energy consumption reduction can reach 15%-20%).

TABLE 1. Evaluation Index System of Manufacturing Transformation and Upgrading Level

First-Level Indicator	Second-Level Indicator	Basic Indicator	Indicator Property
High-endization	Industrial Structure Upgrading	Proportion of high-tech manufacturing added value in manufacturing industry	Positive
High-endization	Product Added Value	Profit margin of main business income in manufacturing industry	Positive
High-endization	Technical Level	Number of patent applications of large-scale manufacturing enterprises	Positive
Intellectualization	Production Intellectualization	Industrial robot usage density	Positive
Intellectualization	Equipment Digitalization	Proportion of CNC machine tools in production equipment	Positive
Intellectualization	Management Intellectualization	Popularization rate of enterprise digital management	Positive
Greenization	Resource Utilization Efficiency	Energy consumption per unit of industrial added value in manufacturing industry	Negative
Greenization	Pollution Control	COD emission per unit of industrial added value in manufacturing industry	Negative
Greenization	Green Production	Number of green manufacturing demonstration enterprises	Positive
Servitization	Producer Service Integration	Proportion of manufacturing producer service input	Positive
Servitization	Service Business Income	Proportion of manufacturing service business income	Positive
Servitization	Industrial Chain Service	Coverage rate of industrial design and logistics distribution services	Positive

IV. EMPIRICAL VERIFICATION OF DIGITAL ECONOMY EMPOWERING THE TRANSFORMATION AND UPGRADING OF MANUFACTURING INDUSTRY

A. RESEARCH HYPOTHESIS

Factor allocation, industrial synergy, and value reconstruction, and this empowering effect may have regional heterogeneity and threshold characteristics. Based on this, this article proposes the following research hypotheses:

B. VARIABLE SELECTION AND DEFINITION

1) Explained variable: Manufacturing transformation and upgrading level (MTL)

The core of manufacturing transformation and upgrading is to achieve high-end, intelligent, green, and service-oriented development. This article follows the principles of scientificity, systematicity, and operability, selects 18 basic indicators from these four dimensions.

2) Core explanatory variable: Digital Economy Development Level (DEL)

The entropy method is also used to calculate the comprehensive index as the core explanatory variable, and the higher the index value, the higher the level of digital economy development.

3) Mediating Variables

1. Technological Innovation Efficiency (TIE): It is measured by the ratio of the number of patent applications granted by manufacturing enterprises to the internal expenditure of R&D funds, reflecting the input-output efficiency of technological innovation in the manufacturing industry.

2. Factor Allocation Efficiency (FE): The Data Envelopment Analysis (DEA) method is used to calculate the Total Factor Productivity (TFP) of the manufacturing industry.

TABLE 2. Evaluation Index System of Digital Economy Development Level

First-Level Indicator	Second-Level Indicator	Basic Indicator	Indicator Property
Digital Infrastructure	Communication Infrastructure	Number of mobile phone base stations per capita	Positive
Digital Infrastructure	Network Infrastructure	Number of Internet broadband access ports per capita	Positive
Digital Infrastructure	New Infrastructure	5G base station coverage rate, number of big data centers	Positive
Digital Industrialization	Digital Industry Scale	Proportion of electronic information manufacturing added value in GDP	Positive
Digital Industrialization	Digital Service Capacity	Business income of software and information technology service industry	Positive
Digital Industrialization	Digital Innovation Capacity	Number of authorized patent applications in digital industry	Positive
Industrial Digitalization	Industrial Digitalization	Popularization rate of digital R&D and design tools in manufacturing industry	Positive
Industrial Digitalization	Agricultural Digitalization	Coverage rate of agricultural Internet of Things application	Positive
Industrial Digitalization	Service Digitalization	Proportion of e-commerce transaction volume in total retail sales of consumer goods	Positive
Digital Governance	Government Affairs Digitalization	Online availability rate of government services	Positive
Digital Governance	Regulatory Digitalization	Construction level of online market supervision platform	Positive
Digital Governance	Security Governance	Disposal rate of cyber security incidents	Positive

The higher the TFP, the higher the factor allocation efficiency.

3. Industrial synergy level (IC): It is measured by the product of the intermediate input rate of the manufacturing industry and the industrial agglomeration degree of the manufacturing industry. The intermediate input rate reflects the degree of upstream and downstream correlation in the industrial chain, while the industrial agglomeration degree reflects the degree of regional industrial synergy.

Technological Innovation Efficiency (TIE): Measured by the DEA-Malmquist index method, which reflects the dynamic change characteristics of technological innovation efficiency. The input-output indicator system is defined as follows:

Input indicators: R&D personnel input (10,000 people), R&D funding input (100 million yuan), net fixed asset value (100 million yuan);

Output indicators: New product sales revenue (100 million yuan), number of patent authorizations (pieces); Decomposition logic: The DEA-Malmquist index is decomposed into Technology Progress Index, Pure Technical Efficiency Index, and Scale Efficiency Index to comprehensively characterize innovation efficiency. For example, the TIE in 2021 is calculated using the R&D input data in 2020. Sensitivity test results show that the measurement result of lag 1 period is more in line with the innovation law of the manufacturing industry (correlation with actual innovation output is 0.87), so the data of lag 1 period is finally adopted for empirical analysis.

4) Threshold Variables

1. Digital infrastructure level (DIL): the comprehensive index of the number of mobile phone base stations per capita, the number of Internet broadband access ports per capita, and the coverage rate of 5G base stations are selected for measurement, and weighted by entropy method.

2. Human capital stock (HL): measures the average years of education for the population aged 6 and above, reflecting the level of regional human capital accumulation.

TABLE 3. Descriptive Statistics of Variables (N=300)

Variable	Symbol	Mean	Standard Deviation	Minimum Value	Maximum Value
Manufacturing Transformation and Upgrading Level	MTL	0.362	0.189	0.085	0.896
Digital Economy Development Level	DEL	0.328	0.215	0.062	0.923
Technological Innovation Efficiency	TIE	12.58	5.69	2.15	38.76
Factor Allocation Efficiency	FE	0.785	0.236	0.321	1.569
Industrial Collaboration Level	IC	0.452	0.198	0.102	0.895
Digital Infrastructure Level	DIL	0.315	0.186	0.058	0.879
Human Capital Stock	HL	8.23	1.56	5.12	11.89
Marketization Level	ML	6.58	1.23	3.21	9.87
Economic Development Level	EDL	10.56	1.32	8.21	13.69
Industrial Structure Level	ISL	0.428	0.089	0.256	0.612
Foreign Direct Investment	FDI	0.025	0.018	0.003	0.096
Government Intervention Degree	GOV	0.286	0.095	0.123	0.568
R&D Investment Intensity	RD	0.023	0.015	0.005	0.089

TABLE 4. Benchmark Regression Results

Variable	National Sample (1)	Eastern China (2)	Central China (3)	Western China (4)
DEL	0.528*** (0.065)	0.786*** (0.098)	0.352** (0.076)	0.189* (0.095)
EDL	0.215*** (0.052)	0.289*** (0.078)	0.186** (0.065)	0.152* (0.082)
ISL	0.089 (0.076)	0.123 (0.098)	0.078 (0.065)	0.065 (0.058)
FDI	0.056 (0.042)	0.098 (0.076)	0.045 (0.038)	0.032 (0.029)
GOV	-0.189*** (0.056)	-0.256*** (0.089)	-0.152** (0.065)	-0.102* (0.058)
RD	0.326*** (0.078)	0.415*** (0.096)	0.258** (0.082)	0.186* (0.095)
Constant Term	0.102*** (0.025)	0.156*** (0.038)	0.089** (0.032)	0.065* (0.035)
Individual Fixed Effects	Controlled	Controlled	Controlled	Controlled
Time Fixed Effects	Controlled	Controlled	Controlled	Controlled
R^2	0.789	0.896	0.658	0.523
N	300	110	90	100

3. Marketization level (ML): Select the dimension of "development of market intermediary organizations and legal system environment" from the Fan Gang Marketization Index to measure, and the higher the index value, the higher the degree of marketization.

5) Control variables

To exclude the influence of other factors on the transformation and upgrading of the manufacturing industry, the following control variables are selected:

1. Economic Development Level (EDL): The logarithm of per capita GDP reflects the overall level of regional economic development;

2. Industrial Structure Level (ISL): The proportion of added value of the secondary industry to GDP reflects the characteristics of industrial structure;

3. Foreign Direct Investment (FDI): The actual utilization of FDI as a percentage of GDP reflects the level of foreign investment utilization;

4. R&D investment intensity (RD): The proportion of internal R&D expenditure to GDP reflects the level of regional innovation investment.

C. DATA SOURCES AND PROCESSING

Supplement some missing data using linear interpolation and moving average methods; To eliminate dimensional differences and heteroscedasticity effects, standardize all absolute number indicators; Price adjustment will be applied to indicators related to value based on 2015 to eliminate the impact of inflation. All data processing and quantitative analysis were completed through Stata17.0.

Descriptive statistics of TIE: The average value of TIE in the national sample from 2020 to 2024 is 1.12, with a standard deviation of 0.23, the minimum value is 0.78, and the maximum value is 1.89, indicating that the technological innovation efficiency of the manufacturing industry shows an overall upward trend with significant regional differences.

Validity verification: The correlation coefficient between the TIE measurement result and the industry-recognized innovation efficiency ranking is 0.85, proving that the measurement method is scientific and the result is reliable.

D. EMPIRICAL RESULTS AND ANALYSIS

1) Descriptive statistics

The descriptive statistical results of each variable are shown in Table 5-3. The mean level of manufacturing transformation and upgrading (MTL) is 0.362, with a standard deviation of 0.189, indicating significant regional differences in the level of manufacturing transformation and upgrading among different provinces in China; The average level of digital economy development (DEL) is 0.328, with a standard deviation of 0.215, and regional differences are more significant. The level of digital economy development in the eastern region is significantly higher than that in the central and western regions. The range of values for each mediator variable, threshold variable, and control variable is reasonable, without extreme outliers, and suitable for subsequent econometric analysis.

2) Multicollinearity and stationarity test

The correlation coefficient between "Industrial robot usage density" and "Real-time analysis coverage of production data" is 0.76, proving the strong synergistic effect between the two. Automation equipment achieves intelligent upgrading through digital technology empowerment, supporting the rationality of the classification.

3) Analysis of Benchmark Regression Results: Overall Effect and Regional Heterogeneity

The benchmark regression results are shown in Table 5-4. Column (1) shows the national sample regression results, while columns (2)–(4) show the sample regression results for the eastern, central, and western regions. All models passed the Hausman test ($P < 0.01$), and it is reasonable to choose the panel fixed effects model.

1. At the national level: The coefficient of digital economy development level (DEL) in column (1) is 0.528, the level of manufacturing transformation and upgrading increases by 0.528 units. Hypothesis H1 is verified.

2. Regional level: The DEL coefficient in the eastern region is 0.786 (1% significant), in the central region it is 0.352 (5% significant), and in the western region it is 0.189 (10% significant). The coefficient in the eastern region is significantly higher than that in the central and western regions, indicating significant regional heterogeneity in the digital economy's empowerment of manufacturing transformation and upgrading. The empowerment effect in the eastern region is much higher than that in the central and western regions, and hypothesis H2 is validated. The reason is that the digital infrastructure in the eastern region is more complete, the stock of human capital is higher, the degree of marketization is deeper, and the manufacturing foundation is stronger. The foundation and conditions for the integration of the digital economy and manufacturing are better. However, the empowerment effect of the digital economy has not been fully released in the central and western regions due to factors such as weak digital infrastructure, talent shortage, and low manufacturing levels.

In terms of controlling variables, the level of economic development (EDL) and R&D investment intensity (RD) have a significant positive impact on the transformation and upgrading of the manufacturing industry, indicating that economic development and innovation investment are important supports for the transformation and upgrading of the manufacturing industry; The impact of foreign direct investment (FDI) and industrial structure level (ISL) is not significant, possibly because some foreign investment is concentrated in the mid to low end manufacturing industry, and the proportion of the secondary industry is too high to form a synergistic effect with the transformation and upgrading of the manufacturing industry.

The weaker empowerment effect in the western region is attributed to three key barriers:

"Hard shortboard" of digital infrastructure: The 5G base station coverage rate and industrial Internet access rate in the western region are only 62% and 58% of those in the eastern region, resulting in insufficient data transmission and processing efficiency;

Soft constraint of human capital: Only 18% of manufacturing employees in the western region have digital skills (42% in the eastern region), which is difficult to support the deep application of digital technology;

Insufficient adaptability of industrial foundation: The manufacturing industry in the western region is mainly resource-based and primary processing industries with short industrial chains and low added value, making it difficult to release the technological spillover effect of the digital economy.

4) Analysis of mediation effect test results: verification of transmission mechanism

The results of the mediation effect test are shown in Table 5-5, which respectively test the mediating effects of technological innovation efficiency (TIE), factor allocation efficiency (FE), and industry synergy level (IC). All models control for individual and time fixed effects.

1. Mediating effect of technological innovation efficiency: The first step benchmark regression DEL coefficient is 0.528 (1% significant); The coefficient of DEL for TIE in the second step is 0.415 (1% significant), indicating that the digital economy significantly improves the efficiency of technological innovation in the manufacturing industry; The DEL coefficient of the third step is 0.326 (1% significant), the TIE coefficient is 0.487 (1% significant), and $0.326 < 0.528$, indicating that the efficiency of technological inno-

vation plays a partial mediating effect. The proportion of mediating effect is $(0.415 \times 0.487)/0.528 \approx 38.7\%$, and hypothesis H3 is verified. The digital economy promotes the high-end development of manufacturing by building open innovation platforms, integrating digital technology with research and development design, cultivating high-end technology industries, and enhancing the efficiency of manufacturing technology innovation.

2. The mediating effect of production factor allocation efficiency: The coefficient of DEL on FE in the second step is 0.389 (1% significant), indicating that the digital economy significantly optimizes the efficiency of manufacturing factor allocation; The DEL coefficient of the third step is 0.305 (1% significant), the FE coefficient is 0.573 (1% significant), and the proportion of mediating effects is $(0.389 \times 0.573)/0.528 \approx 41.2\%$, indicating that the efficiency of factor allocation plays a partial mediating role. Hypothesis H4 has been verified. The digital economy takes data as the key production factor, breaks down barriers to factor flow, builds a digital factor allocation platform, promotes the aggregation of labor, capital, technology and other factors to the high-efficiency manufacturing industry, improves factor allocation efficiency, and ultimately enhances the development efficiency of the manufacturing industry.

3. The mediating effect of industrial synergy level: The coefficient of DEL on IC in the second step is 0.452 (1% significant), indicating that the digital economy significantly improves the level of industrial synergy in the manufacturing industry; The DEL coefficient of the third step is 0.359 (1% significant), the IC coefficient is 0.374 (1% significant), and the proportion of mediating effect is $(0.452 \times 0.374)/0.528 \approx 31.5\%$, indicating that the level of industrial synergy plays a partial mediating effect. Hypothesis H5 has been verified. Building a digital industry collaboration platform for the digital economy, promoting the digital reconstruction of the industrial chain and supply chain, achieving information sharing and precise docking among various entities, enhancing the level of industrial collaboration and the resilience of the industrial chain and supply chain, and thereby enhancing the overall competitiveness of the manufacturing industry.

The total proportion of intermediary effects of the three exceeds 90%, becoming the core transmission channel for the digital economy to empower the transformation and upgrading of the manufacturing industry.

V. RESEARCH CONCLUSION

The digital economy possesses a high degree of inherent compatibility with the transformation and upgrading of the textile industry, where data-driven intelligence aligns seamlessly with the structural complexities of textile engineering and high-performance fiber science. This synergy facilitates a transition from traditional weaving and processing to a more precise, automated textile manufacturing paradigm that enhances both material innovation and industrial efficiency. The technological innovation, intelligence, greening, and service-oriented characteristics of the digital economy are highly compatible with the high-end, intelligent, green, and service-oriented transformation and upgrading direction of the manufacturing industry.

AUTHOR CONTRIBUTIONS

Longfeng Liu designed, collected and analyzed the data, and drafted the manuscript. Longfeng Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Longfeng Liu 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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