# The Impact of Digital Innovation on the International Competitiveness of Manufacturing: An Empirical Study Based on Different Factor-Intensive Industries

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**Abstract: Based on the panel data of 11 provinces and cities in the Yangtze River Economic Belt of China from 2011 to 2020, this paper first establishes a digital innovation evaluation system from two aspects: the foundation and ability of digital innovation. Then, in manufacturing industry, four indicators such as the trade competition index are used to measure its international competitiveness. On this basis, a model is constructed to empirically analyze the impact of digital innovation on the international competitiveness of different factor-intensive industries in the manufacturing industry. The results show that the digital innovation foundation has a significant positive promoting effect on the international competitiveness of different factor-intensive industries. While the digital innovation ability has a significant positive promoting effect on the international competitiveness of capital-intensive industries, it has a remarkable inhibiting impact on that of labor-intensive industries, and has no significant impact on that of technology-intensive industries. On this basis, this paper proposes relevant strategies to enhance the international competitiveness of different factor-intensive industries by improving the level of digital innovation.**

**Keywords: Digital Innovation; International Competitiveness; Manufacturing Industry; Yangtze River Economic Belt**

## 1. Introduction

In recent years, the digital economy has gradually become an important force driving technological and industrial transformation. China proposes to promote the deep integration of the digital economy and the real economy, and build industrial clusters with international competitiveness. However, China's low-end manufacturing industry based on cheap labor in the past is difficult to maintain long-term stable growth, and the manufacturing industry urgently needs to transform and upgrade.

The international competitiveness of an industry refers to the ability of a country's industry to effectively allocate production factors and resources in the process of international market competition, thereby possessing the ability to explore and occupy the market, as well as the ability to produce more wealth than its competitors and improve the overall social welfare level of the country[1]. In existing research, there are methods for calculating competitiveness indices based on trade value added[2], analyzing international competitiveness based on the status of global value chain division of labor[3], and constructing indicator systems such as export contribution rate[4] and specialization[5] to comprehensively evaluate the international competitiveness of the manufacturing industry. Digital innovation refers to the use of digital technologies such as artificial intelligence, big data, and cloud computing for new product development, production processes, organizational model changes, and business model innovation[6,7]. It is divided into process digital innovation and output innovation[8]. There is still little research on the impact of digital innovation on the international competitiveness of the manufacturing industry. The main literature supports the effects of digital transformation on competitiveness[9] and on the optimization and upgrading of the manufacturing industry[10].

In conclusion, digital innovation and the international competitiveness of the manufacturing industry have drawn substantial attention from researchers, leading to certain research accomplishments. There are already numerous research findings on the connotation and evaluation of the international competitiveness, and several relatively authoritative evaluation index systems exist,

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which possess good reference value. Moreover, existing research predominantly conducts empirical analyses on its impact on the competitiveness of the manufacturing industry from aspects such as industrial digitization, digital transformation, 5G technology, and informatization. The research results exhibit differentiated conclusions, including positive and negative effects. However, there is still a dearth of research that combines digital innovation and the international competitiveness of the manufacturing industry. Additionally, there is insufficient quantitative research on the digital innovation evaluation system and a lack of a unified measurement standard. Based on this, this paper constructs an index system of digital innovation suitable for the provincial and municipal levels, conducts in-depth research on the impact of digital innovation on the international competitiveness of different factor-intensive industries in the manufacturing industry, and puts forward suggestions for enhancing the international competitiveness.

## 2. Measurement of Digital Innovation

Regarding the index system of digital innovation, although there is currently no unified measurement standard for digital innovation, most scholars regard digital innovation foundation and digital innovation ability as one of the important measurement criteria[11]. In view of this, this paper constructs an index system with the foundation of digital innovation and the ability of digital innovation to evaluate digital innovation, including a total of 10 secondary indicators and 15 tertiary indicators.

This paper uses the entropy weight method to measure the weights of 15 tertiary indicators of digital innovation. The specific method is as follows: first, the collected original data is standardized and shifted and recorded as $X_{ij}$, which represents the value of this indicator in region j in year i. Then, calculate the contribution degree of this indicator in region j in year i to the whole $P_{\mathrm{ij}} = \frac{X_{\mathrm{ij}}}{\sum_{\mathrm{ij}} X_{\mathrm{ij}}}$. Then calculate the entropy value of this indicator $E = k \sum_{\mathrm{ij}} P_{\mathrm{ij}} \ln (P_{\mathrm{ij}})$. Here, $k = \frac{1}{\ln (mn)}$ is a constant (in this study, m represents 10 years and n represents 11 provinces and cities). Similarly, calculate the entropy values $E_t$ of the other 14 indicators (t represents 15 subdivided indicators), and obtain the weights of 15 indicators respectively $W_{\mathrm{t}} = \frac{1-E_{\mathrm{t}}}{\sum_{\mathrm{t}} (1-E_{\mathrm{t}})}$. Finally, combined with the data $X_{ij}$ obtained after translation processing and the calculated entropy weight $W_t$, the digital innovation foundation index and digital innovation ability index of each province and city in each year are obtained by weighted summation $U_{ij} = \sum_t W_t X_{ij}$.

Table 1 shows the digital innovation foundation of various provinces and cities in the Yangtze River Economic Belt of China. Judging from the overall data, during the period from 2011 to 2020, the digital innovation foundation level basically showed a strong upward trend. As time goes by, the provinces with relatively backward digital innovation foundation levels develop rapidly and gradually shorten the gap with provinces such as Shanghai. Since 2019, the comprehensive scores are all higher than 0.210. In terms of the average annual growth rate of the digital innovation foundation level, Jiangxi and Guizhou are higher than 20.000%, and the digital innovation foundation level shows an obvious upward trend; while Shanghai, Jiangsu and Zhejiang are all lower than the regional average of 11.701%, and the digital innovation foundation level rises relatively gently.

According to table 2, during the period from 2011 to 2020, the digital innovation ability showed a stable upward trend. Among them, Shanghai has the highest comprehensive score of digital innovation ability, followed by Zhejiang, Jiangsu and Sichuan Province, etc., while Yunnan Province has a relatively low comprehensive score of digital innovation ability. In terms of the average annual growth rate of the digital innovation foundation level, Jiangxi Province and Anhui Province are higher than 13.000%, and the digital innovation ability shows an obvious upward trend; while Shanghai, Jiangsu, Zhejiang and Sichuan Province are all lower than the regional average of 7.528%, and the digital innovation ability rises relatively gently.

## 3. Measurement of International Competitiveness

China's export volume of goods trade is statistically based on international trade product categories (HS), which is different from the national economic standard industry classification (GB) used in manufacturing statistics. Following the practice of Li et al. (2021), this paper corresponds various product export volumes one by one with the segmented industries of manufacturing[12].

Most existing studies construct an evaluation index system for international competitiveness from the perspectives of scale, benefit and potential. This paper mainly draws on the research of He et al. (2018) and selects four index as indicators for evaluating international competitiveness[13]. This paper also uses the entropy weight method to measure the international competitiveness of three different factor-intensive industries in the Yangtze River Economic Belt. The specific method steps have been explained in the previous text and will not be repeated here. The calculation results of the weights of various indicators are shown in Table 3.

**Table 1. The Digital Innovation Foundation**

| region | 2011 | 2013 | 2015 | 2017 | 2019 | Average value | average annual growth rate |
|---|---|---|---|---|---|---|---|
| Shanghai | 0.20 | 0.25 | 0.26 | 0.29 | 0.31 | 0.272 | 5.495% |
| Jiangsu | 0.19 | 0.24 | 0.27 | 0.30 | 0.32 | 0.271 | 6.201% |
| Zhejiang | 0.19 | 0.23 | 0.28 | 0.30 | 0.33 | 0.272 | 6.462% |
| Anhui | 0.08 | 0.14 | 0.18 | 0.23 | 0.26 | 0.189 | 14.437% |
| Jiangxi | 0.03 | 0.09 | 0.14 | 0.19 | 0.23 | 0.148 | 24.732% |
| Hubei | 0.09 | 0.14 | 0.19 | 0.23 | 0.26 | 0.190 | 12.349% |
| Hunan | 0.07 | 0.12 | 0.16 | 0.20 | 0.24 | 0.167 | 15.305% |
| Chongqing | 0.07 | 0.12 | 0.16 | 0.20 | 0.23 | 0.163 | 15.299% |
| Sichuan | 0.09 | 0.15 | 0.20 | 0.23 | 0.28 | 0.199 | 14.013% |
| Guizhou | 0.04 | 0.09 | 0.15 | 0.19 | 0.23 | 0.147 | 20.148% |
| Yunnan | 0.05 | 0.11 | 0.15 | 0.18 | 0.22 | 0.152 | 17.221% |
| regional average value | 0.10 | 0.15 | 0.19 | 0.23 | 0.27 | 0.197 | 11.701% |

**Table 2. The Digital Innovation Ability**

| region | 2011 | 2013 | 2015 | 2017 | 2019 | Average value | average annual growth rate |
|---|---|---|---|---|---|---|---|
| Shanghai | 0.38 | 0.47 | 0.55 | 0.55 | 0.56 | 0.511 | 4.429% |
| Jiangsu | 0.39 | 0.46 | 0.48 | 0.49 | 0.51 | 0.473 | 3.107% |
| Zhejiang | 0.36 | 0.43 | 0.47 | 0.49 | 0.50 | 0.458 | 3.769% |
| Anhui | 0.14 | 0.21 | 0.31 | 0.34 | 0.40 | 0.294 | 13.066% |
| Jiangxi | 0.10 | 0.15 | 0.24 | 0.24 | 0.28 | 0.210 | 13.143% |
| Hubei | 0.17 | 0.31 | 0.38 | 0.43 | 0.44 | 0.361 | 11.253% |
| Hunan | 0.17 | 0.22 | 0.29 | 0.30 | 0.33 | 0.276 | 8.810% |
| Chongqing | 0.21 | 0.29 | 0.37 | 0.42 | 0.45 | 0.363 | 9.271% |
| Sichuan | 0.27 | 0.34 | 0.42 | 0.46 | 0.48 | 0.406 | 6.535% |
| Guizhou | 0.10 | 0.17 | 0.24 | 0.26 | 0.27 | 0.227 | 12.556% |
| Yunnan | 0.08 | 0.15 | 0.22 | 0.23 | 0.23 | 0.187 | 11.932% |
| regional average value | 0.22 | 0.29 | 0.36 | 0.38 | 0.41 | 0.342 | 7.528% |

**Table 3. Manufacturing International Competitiveness Indicators and Weights for Three Different Factor-Intensive Industries**

| first-level indicator | second-level indicator | labor-intensive industries | capital-intensive industries | technology-intensive industries |
|---|---|---|---|---|
| international competitiveness | trade competition | 0.093 | 0.172 | 0.101 |
| | revealed comparative advantage | 0.240 | 0.152 | 0.280 |
| | international market share | 0.428 | 0.427 | 0.335 |
| | intra-industry trade | 0.238 | 0.248 | 0.283 |

## 4. Model Analysis

### 4.1 Model Specification

To verify the impact of digital innovation on the international competitiveness of the manufacturing industry, this paper examines the impact of digital innovation on the international competitiveness of different factor-intensive manufacturing industry. The empirical test model is set as follows.

$$lnIC_{it} = \beta_0 + \beta_1 lnIDB_{it} + \beta_2 lnIDC_{it} + \beta_3 lnRSI_{it} + \beta_4 lnFDI_{it} + \beta_5 lnMS_{it} + \varepsilon_{it} \quad (1)$$

Where i represents a province or city, t represents a year, *IC* represents international competitiveness, *IDB* represents the foundation of digital innovation, *IDC* represents digital innovation ability, *RSI* represents related and supporting industries, *FDI* represents foreign direct investment, and $MS$ represents market scale. $\beta_0$ is the intercept term and $\varepsilon_{it}$ is the random error term. In order to ensure the goodness of fit of the model and effectively reduce the problem of heteroscedasticity, take the natural logarithm of each variable.

### 4.2 Variable Selection and Data Source

In order to empirically test the impact of digital innovation foundation and digital innovation ability on the international competitiveness of different factor-intensive industries, this paper sequentially designs the explained variables. $IC_1$ is the international competitiveness index of labor-intensive industries, $IC_2$ is the international competitiveness index of capital-intensive industries, and $IC_3$ is the international competitiveness index of technology-intensive industries. The original research data comes from the cargo trade data from 2011 to 2020 in the international trade research and decision support system of the Development Research Center of China. Then, according to the methods mentioned earlier, the international competitiveness values of the three factor-intensive industries are calculated annually.

The explanatory variable of digital innovation is mainly constituted by two aspects: digital innovation foundation (*IDB*) and digital innovation ability (*IDC*), encompassing a total of 10 secondary indicators and 15 tertiary indicators. According to the methods described earlier, the values of the digital innovation foundation and digital innovation ability are calculated annually. The control variables include related and supporting industries (*RSI*), foreign direct investment (*FDI*), and market size (*MS*). Among them, related and supporting industries (*RSI*) is measured by the added value of the secondary industry; foreign direct investment (*FDI*) is measured by the actual amount of foreign direct investment received; market size (*MS*) is measured by the total population. The research data is sourced from the National Bureau of Statistics, statistical yearbooks of various provinces and cities, and the "Peking University Digital Inclusive Finance Index Report." For some missing data, the moving average method is employed for supplementation.

## 5. Empirical Analysis

### 5.1 Model Pre-Test

This paper uses six unit root test methods such as the LLC method to conduct panel unit root tests on the international competitiveness indexes of different factor-intensive industries and follows the principle of the minority being subordinate to the majority. According to Table 4, all variables are stationary series at the level, and there is no need for further panel co-integration tests. All the results in this part are calculated according to Eviews11.0 while *, **, and *** indicate significance levels of 10%, 5%, and 1% respectively.

**Table 4. Panel Unit Root Test Results for Different Factor-Intensive Industries**

| variables | LnIC1 | LnIC2 | LnIC3 |
|---|---|---|---|
| LLC | -3.585*** | -10.898*** | -7.159*** |
| Breitung | 0.636 | -4.884*** | -3.658** |
| IPS | -1.568* | -2.051** | -2.556*** |
| Frisher-ADF | 40.873*** | 55.158*** | 42.438*** |
| Frisher-PP | 44.322*** | 54.664*** | 51.360*** |
| Hadri | 5.357 | 6.472 | 4.509 |
| result | Stationary series at level | Stationary series at level | Stationary series at level |

The selection results of panel estimation methods for models of different factor-intensive industries are shown in Table 5. The models for labor-intensive and capital-intensive industries finally choose the two-way fixed effect model, and the model for technology-intensive industries finally chooses the cross-section fixed and time-period random model.

**Table 5. Selection Results of Panel Estimation Methods for Different Factor-Intensive Industries**

| industry | test method | test indicator | statistical value |
|---|---|---|---|
| labor-intensive industries | likelihood ratio test | F | 21.401*** |
| | Hausman | Hausman | 0.000 |
| | Hausman | Hausman statistic value (period) | 21.496*** |
| | Hausman | Hausman statistic value (cross-section) | 34.063*** |
| capital-intensive industries | likelihood ratio test | F | 26.485*** |
| | Hausman | Hausman | 0.000 |
| | Hausman | Hausman statistic value (period) | 15.682*** |
| | Hausman | Hausman statistic value (cross-section) | 14.794** |
| technology- | likelihood | F | 19.304*** |

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| | | | |
|---|---|---|---|
| intensive industries | ratio test | | |
| | Hausman | Hausman | 0.000 |
| | Hausman | Hausman statistic value (period) | 2.626 |
| | Hausman | Hausman statistic value (cross-section) | 13.729** |

This paper conducts cross-sectional correlation tests and panel heteroscedasticity tests on the relevant panel data of different factor-intensive industries. The results are shown in Table 6. The models of labor-intensive industries and capital-intensive industries both have cross-sectional heteroscedasticity. Therefore, Cross-section weights is finally selected for the variance-covariance robust estimation of parameter estimators. The model of technology-intensive industries has cross-sectional correlation and cross-sectional heteroscedasticity. Therefore, White Cross-section is finally selected for the variance-covariance robust estimation of parameter estimators.

**Table 6. Test Results of Panel Data Model for Different Factor-Intensive Industries**

| Industry | Test method | Statistical value |
|---|---|---|
| labor-intensive industries | Cross-section correlation test | -0.704 |
| | Cross-section heteroscedasticity test | 100.149*** |
| | Time period heteroscedasticity test | 2.588 |
| capital-intensive industries | Cross-section correlation test | -1.357 |
| | Cross-section heteroscedasticity test | 76.132*** |
| | Time period heteroscedasticity test | 3.811 |
| technology-intensive industries | Cross-section correlation test | 10.124*** |
| | Cross-section heteroscedasticity test | 80.651*** |
| | Time period heteroscedasticity test | 9.276 |

## 5.2 Empirical Results

Table 7 summarizes the regression results of three factor-intensive industries. The regression results are analyzed separately as follows.

**Table 7. Regression Results of Three Factor Intensity Industries**

| variables | labor-intensive industries | capital-intensive industries | technology-intensive industries |
|---|---|---|---|
| C | -0.467 | -0.589*** | 0.583*** |
| LnIDB | 0.421* | 0.969*** | 1.000* |
| LnIDC | -0.252*** | 0.219** | 0.389* |
| LnRSI | 0.408*** | -0.325*** | 0.735*** |
| LnFDI | -0.027 | -0.102** | -0.117* |
| LNMS | 3.039*** | 0.010 | -1.055*** |
| $R^2$ | 0.974 | 0.967 | 0.922 |
| F | 133.944*** | 183.356*** | 74.445*** |

For labor-intensive industries, the $R^2$ value is 0.974, indicating a good degree of model fitting. The regression coefficient of digital innovation foundation is 0.421 which means that under the condition that other independent variables remain unchanged, every 1% increase in the digital innovation foundation can increase the international competitiveness index of labor-intensive industries by 0.421%. The regression coefficient of digital innovation ability is -0.252 which shows that digital innovation ability has a significant inhibitory effect on the international competitiveness of labor-intensive industries. That is, under the condition that other independent variables remain unchanged, every 1% increase in digital innovation ability will reduce the international competitiveness index of labor-intensive industries by 0.252%. The control variables related and supporting industries and market scale have a significant positive effect on the international competitiveness of labor-intensive industries. However, foreign direct investment does not pass the significance test.

For capital-intensive industries, the $R^2$ value is 0.967, indicating a good degree of model fitting. The regression coefficient of digital innovation foundation is 0.969 which means that under the condition that other independent variables remain unchanged, every 1% increase in the digital innovation foundation will increase the international competitiveness index of capital-intensive industries by 0.969%. The regression coefficient of digital innovation ability is 0.219 which shows that under the condition that other independent variables remain unchanged, every 1% increase in digital innovation ability will increase the international competitiveness index of capital-intensive industries by 0.219%. The control variables related and supporting industries and foreign direct investment have a significant inhibitory effect on the international competitiveness of capital-intensive industries.

However, market size does not pass the significance test.

For technology-intensive industries, the $R^2$ value is 0.922, indicating a good degree of model fitting. The regression coefficient of digital innovation foundation is 1.000, indicating that under the condition that other independent variables remain unchanged, every 1% increase in the digital innovation foundation will increase the international competitiveness index of technology-intensive industries by 1.000%. The regression coefficient of digital innovation ability is 0.389, indicating that under the condition that other independent variables remain unchanged, every 1% increase in digital innovation ability will increase the international competitiveness index of technology-intensive industries by 0.389%. The control variable related and supporting industries has a significant positive effect on the international competitiveness of technology-intensive industries. In addition, foreign direct investment and market size both have a significant inhibitory effect on the international competitiveness of technology-intensive industries.

### 5.3 Comparison of Empirical Results

The research results show that the digital innovation foundation has a significant positive promoting effect on the international competitiveness of different factor-intensive industries. Among them, the influence of the digital innovation foundation on the international competitiveness of capital-intensive industries (regression coefficient is 0.969) and technology-intensive industries (regression coefficient is 1.000) is relatively similar, while that of labor-intensive industries (regression coefficient is 0.421) is relatively small. Digital innovation ability has a remarkable inhibiting impact on the international competitiveness of labor-intensive industries (regression coefficient is -0.252), and has a remarkable positive promoting effect on that of capital-intensive and technology-intensive industries (regression coefficients are 0.219 and 0.389 respectively).

## 6. Conclusions and Suggestions

According to the research results mentioned earlier, this paper presents the following strategies:

First, all regions should improve and strengthen the establishment of digital innovation infrastructure to promote the comprehensive digital transformation process in Yangtze River Economic Belt. Firstly, increase capital and research and development investment in digital infrastructure in regions with relatively weak foundations and establish a digital infrastructure support system. In particular, fully leverage China's leading edge in 5G research and development and expand the application fields of 5G. Secondly, promote the integration of new information technologies such as digital twins and traditional infrastructure and let the industrial Internet play a leading and supporting role throughout the industrial chain of three factor-intensive industries.

Second, all regions should enhance scientific and technological innovation capabilities and cultivate application-oriented talents with digital skills. Firstly, increase capital investment and research and development efforts in key scientific fields such as intelligent manufacturing and network data security, accelerate the breakthrough of key technologies, break foreign technology monopolies, and form their own competitive advantages. Secondly, continuously promote application-oriented colleges and universities to cultivate professional digital skills talents for enterprises and explore more and better school-enterprise cooperation and research methods to help enterprises carry out digital innovation and form unique competitive advantages for enterprises.

Third, all regions should jointly establish a development cooperation mechanism and introduce relevant policies to provide institutional guarantees. Firstly, effectively give play to the leading role of provinces with high levels of digital innovation such as Jiangsu, Zhejiang, and Shanghai. While maintaining their original development advantages, through government referrals, share resources and experiences with relatively backward regions to comprehensively improve the digital innovation foundation level and digital innovation ability of all regions. Secondly, to address the issue of the decelerated growth rate of with relatively high levels of digital innovation, special plans can be established to guide outstanding digital intelligent manufacturing enterprises to play a leading role in the industry and drive the transformation and reform of other small, medium, and micro enterprises in the region. Thirdly, the intellectual property protection system should be reformed and improved in an

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all-round way at multiple levels, the digital reform of government services should be promoted, the government's supervision ability should be enhanced, supervision costs should be reduced, and the sharing of regional government service data resources should be accelerated.

This paper has conducted in-depth research on the impact of digital innovation foundation and digital innovation ability on the international competitiveness of three different factor-intensive industries. It has certain practical significance for enhancing the international competitiveness of the manufacturing industry. However, there are still some shortcomings. Firstly, due to the limited sample size, the sample has not been further divided into different regions for empirical analysis and comparison, so the empirical results are not comprehensive enough. Secondly, due to the lack of some data, the established digital innovation evaluation index system is not detailed and perfect enough.

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