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Digital Economy Development and Export Trade Complexity: The Mediating Effect of Technological Innovation

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Abstract: Against the backdrop of increasingly complex global economic conditions, intensifying trade frictions, and rising trade barriers, this paper uses panel data from 30 provinces and municipalities in China over an 11-year period to construct a digital economy indicator system and empirically examine the relationship among the digital economy, technological innovation, and export trade complexity. The results indicate that the development of the digital economy can significantly enhance the technological complexity of exports, thereby improving a country's position in international trade. These findings remain robust after a series of robustness tests, including replacing explanatory variables and introducing lagged digital economy development indicators. Mechanism analysis shows that the development of the digital economy significantly promotes the level of innovation, which in turn increases the technological complexity of export products through innovation. Heterogeneity analysis reveals that the positive effect of the digital economy on export technological complexity is more pronounced in eastern regions, while the transformation efficiency of innovation outcomes in central regions remains relatively limited and the digital economy infrastructure in western regions is still underdeveloped. Further analysis employs a machine learning random forest model to examine the nonlinear relationship between the digital economy and export technological complexity. The results are analyzed and interpreted using optimal feature selection, relative feature importance ranking, partial dependence plots, and decision tree models.

Keywords: Digital economy; Export technological complexity; Machine learning.

1. Introduction

Since China's accession to the WTO, the country has continued to expand its openness to the outside world. Overseas markets have been rapidly expanded, enabling China to maintain its position as the world's largest trader in goods for seven consecutive years, while remaining the world's second-largest consumer market, the largest online retail market, and the second-largest import market globally. In the 14th Five-Year Plan, the Outline of the Long-Range Objectives Through 2035, and the 14th Five-Year Plan for High-Quality Development of Foreign Trade, the Chinese government emphasizes accelerating the establishment of a new development pattern in which the domestic circulation plays the dominant role while domestic and international circulations reinforce each other. Foreign trade plays a crucial role in promoting China's high-quality economic development. Improving China's position in the international division of labor and occupying the high-end segments of global industrial chains require innovation as the primary driving force, while the digital economy has become an important pillar of modern economic development.

Amid the combined impacts of global economic slowdown, the Russia–Ukraine conflict, the Red Sea crisis, and the COVID-19 pandemic, international trade costs have increased and trade volumes have contracted. Countries have strengthened trade barriers to maximize their own interests. Under such circumstances, how to enhance the competitiveness of a country's export products in the international market and thereby improve its position in international trade has become an issue worthy of in-depth investigation.

Through a systematic analysis of the relationships among the digital economy, technological progress, and international trade, this paper explores how the development of the digital economy promotes technological progress and consequently increases the technological complexity of a country's export products, thereby improving its position in international trade. The study aims to provide both theoretical support and empirical evidence for the high-quality development of China's foreign trade.

2. Theoretical Foundations and Literature Review

Adam Smith's theory of absolute advantage argues that a country should produce and export goods with lower absolute production costs in international trade, while importing and using goods with higher absolute production costs. David Ricardo's theory of comparative advantage further suggests that a country should export goods with lower opportunity costs and import goods with higher opportunity costs in trade. The factor endowment theory holds that a country should export goods that intensively use its relatively abundant factors of production and import goods that intensively use its relatively scarce factors. This theory also posits that under conditions of free trade, international trade can gradually equalize factor prices across countries. Although these classical trade theories promoted the development of international trade for a certain period, they did not incorporate technological progress into their analytical frameworks.

In 1961, Posner first introduced technological progress into international trade theory and proposed the technology gap theory of trade. This theory argues that technological progress

can give a country a temporary advantage in international trade in the short run. However, in the long run, other countries may acquire the same technology through imitation, thereby eroding the innovating country's comparative advantage. Vernon further integrated the product life cycle theory with technological factors to explain the impact of technological progress on international trade. He divided the development process into three stages. First, in the innovation stage, the innovating country obtains monopoly profits through technological innovation. Then, as the industry develops and the domestic market gradually becomes saturated, firms must expand into overseas markets to gain more profits, and the innovating country begins exporting products abroad. Finally, as the industry continues to develop and product production becomes standardized, firms seek lower production costs and therefore shift production to developing countries with abundant labor resources; at this stage, the innovating country becomes an importer.

Chen Jianguo (2004) argues that a country without innovation capabilities will inevitably remain in a disadvantaged position in international trade in terms of living standards. Technological innovation can generate economies of scale, increasing returns to scale, and imperfect competition. In the short term, obtaining monopoly profits through innovation becomes a necessary condition for a country to promote technological innovation.

In the early stage, foreign scholars such as Stern and Maskus (1981) and Wakelin (1998), as well as Chinese scholars including Li Limin and Fang Miaojie (2007) and Yu Guizhuang (2011), empirically examined the relationship between innovation and international trade [5, 6, 9]. Their studies show that indicators of innovation—such as the number of patent applications, R&D investment, and the number of scientists—can significantly promote a country's international trade volume. However, with the continuous improvement of people's living standards, measuring the quality of international trade solely from the perspective of trade volume has become insufficient. Therefore, building on the ideas of Hausmann, scholars such as Xu Wei et al. (2022) and Yin Huahe and Liu Yanyan (2022) proposed methods for measuring export technological complexity [10, 11].

Export technological complexity refers to the R&D intensity, technological sophistication, and value-added embodied in a country's export products. It has gradually become an important indicator for measuring the quality of international trade.

A review of the existing literature shows that current studies on technological innovation and international trade still mainly focus on empirical analyses of trade volume. However, as China's economy transitions from a phase of rapid growth to a new stage of high-quality development, the necessity of studying high-quality international trade has become increasingly evident. High-quality international trade not only involves the expansion of trade volume but also encompasses the optimization of trade structure, the increase in product value-added, the enhancement of technological content, and innovations in trade modes. Therefore, drawing on previous studies, this paper employs export technological complexity as a key indicator to measure the level of high-quality international trade. The higher the technological complexity of exports, the more likely a country exports high value-added products, occupies a higher position in the global value chain, and obtains greater profits.

As an important driving force in building a modern economic system, the digital economy has attracted increasing academic attention. Existing studies on the relationships among the digital economy, technological progress, and international trade mostly focus on the interactions between two of these factors, while relatively few studies incorporate all three within a unified analytical framework. This lack of an integrated perspective limits our comprehensive understanding of how the digital economy influences international trade through technological progress. Therefore, the first contribution of this paper is to incorporate the digital economy, technological progress, and export technological complexity into a unified empirical framework to explore the relationships among them.

At present, a substantial body of empirical research has examined the relationship between the digital economy and innovation. Existing studies have verified the promoting effect of the digital economy on innovation performance through empirical analysis. However, most of these studies mainly focus on empirical evidence and lack systematic theoretical and mathematical model support. Based on this gap, the second contribution of this paper is to systematically demonstrate, through mathematical modeling, the mechanism by which the digital economy promotes technological progress, thereby providing theoretical support for the empirical findings that the digital economy drives technological advancement.

Finally, using provincial panel data, this paper is among the first to apply a machine learning random forest model to explore the nonlinear relationship between the digital economy and export technological complexity. By comparing its explanatory power with that of traditional influencing factors, this study further reveals the relative importance of the digital economy. This not only helps enrich the theoretical understanding of the mechanisms linking the digital economy and international trade but also provides policy implications for promoting the high-quality development of international trade. This constitutes the third contribution of this paper.

3. Theoretical Analysis and Model Derivation

3.1. Theoretical Analysis

There exists a complex coupling relationship between technological progress and international trade.

From the perspective of exporting countries, technological progress can significantly promote international trade. First, technological progress improves production efficiency and reduces production costs, thereby enhancing the competitiveness of a country's products in international markets. Second, advanced technology can improve the quality of export products and increase their value-added, which helps expand international market demand and creates more export opportunities. Third, the application of technological progress in fields such as information and communication technology and e-commerce simplifies international trade procedures, improves transaction efficiency, and reduces transportation and management costs in international trade.

From the perspective of importing countries, import trade provides a more direct channel for technological progress. First, by importing high-tech products and equipment, a country can directly acquire advanced technologies and production processes, thereby promoting the improvement of domestic technological capabilities. Second, firms in the

importing country can analyze and study imported products to learn advanced technologies and management experience, which further stimulates domestic technological innovation and technological upgrading. Third, import trade introduces international market competition, which forces domestic firms to improve their technological level and innovation capacity in order to cope with increasingly intense competition.

In summary, technological progress and international trade exhibit mutually reinforcing effects. However, for a developing country, relying solely on importing technology is not a sustainable strategy for improving its position in the international division of labor and achieving long-term national development. Only by achieving breakthroughs through technological innovation—from imitation to independent innovation—can a country ultimately realize the high-quality development of exports.

3.2. Mathematical Derivation of the Digital Economy's Effect on Green Technological Innovation

Drawing on the studies of Bai Xuejie (2021) and Yi Xin (2015), this paper assumes the existence of three product sectors: upstream, midstream, and downstream sectors [12, 13].

The upstream sector adopts a CES production technology.

$$Y_t = \left(\sum_{i=1}^{n} \varphi_i Y_{it}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

Y_t denotes the output produced by the upstream firm, and Y_{it} represents the intermediate input from the $i-th$ midstream industry required by the upstream firm. φ_i denotes the share of the intermediate product from industry i used in the upstream firm's production, satisfying $\sum_{i=1}^{n} \varphi_i = 1$ with $\varphi_i > 0$. The parameters satisfy $\varepsilon > 1$ and $1 - \varepsilon > 0$, indicating that the intermediate inputs Y_{it} exhibit both substitutability and complementarity. The upstream firm chooses Y_{it} to maximize its profit.

Suppose there are n midstream industries in the economy and the market is perfectly competitive. Each midstream firm i is assumed to adopt a Cobb–Douglas production function.

$$Y_{it} = L_{it}^{1-\alpha} \int_0^1 A_{it}^{1-\alpha}(j) x_{it}^{\alpha}(j) dj \tag{2}$$

L_{it} denotes labor input, satisfying the labor endowment constraint $L_t = \sum_{i=1}^{n} L_{it}$. $x_{it}(j)$ represents the quantity of the $j-th$ input factor used in production. Since production is carried out by downstream firms, $A_{it}(j)$ denotes the level of technology.

Let the probability of successful R&D for input product Y_{it} be $\lambda_{it}(j)$, and the technological improvement level be γ_{it}. Following the study of Xue Haotao et al., and in order to avoid the scale effect in production, the success probability is specified as follows:

$$\tau_{it}(j) = \lambda_i \left[\frac{R_{it}(j)}{L_{it} A_{it}^{*}(j)} \right]^{\frac{1}{2}} \tag{3}$$

Where $R_{it}(j)$ denotes R&D investment, $A_{it}^{*}(j)$ represents the innovation target, and λ_i denotes R&D efficiency, with $\lambda_i > 0$.

The R&D efficiency of input j increases with the development of the digital economy Dig_{it} and the degree of matching between the digital economy and the industry Mat_{it}. Let θ denote the efficiency parameter. Accordingly, the R&D efficiency can be expressed as follows:

$$\lambda_i = \theta Dig_{it}^{\beta_1} Mat_{it}^{\beta_2} \tag{4}$$

Where β_1 and β_2 are efficiency parameters, both greater than zero.

The optimization problem of the midstream firm is given by:

$$max. P_{it} L_{it}^{1-\alpha} \int_0^1 A_{it}^{1-\alpha}(j) x_{it}^{\alpha}(j) dj - W_{it} L_{it} - \int_0^1 P_{it}(j) x_{it}(j) dj \tag{5}$$

From the first-order condition, we obtain:

$$P_{it}(j) = \alpha P_{it} L_{it}^{1-\alpha} A_{it}^{1-\alpha}(j) x_{it}^{\alpha-1}(j) \tag{6}$$

$$W_{it} = (1-\alpha) P_{it} L_{it}^{-\alpha}(j) x_{it}^{\alpha}(j) dj \tag{7}$$

At this point, the optimal behavior of the midstream firm can be expressed as:

$$max. P_{it}(j) x_{it}(j) - P_{it} x_{it}(j) \tag{8}$$

Substituting equation (6) into equation (8), we obtain:

$$max. P_{it} L_{it}^{1-\alpha} A_{it}^{1-\alpha}(j) x_{it}^{\alpha}(j) - P_{it} x_{it}(j) \tag{9}$$

Taking the derivative and setting it equal to zero, we obtain:

$$x_{it}(j) = \alpha^{\frac{2}{1-\alpha}} A_{it}(j) L_{it} \tag{10}$$

$$P_{it}(j) = \frac{P_{it}}{\alpha} \tag{11}$$

Substituting equations (10) and (11) into equation (8), we obtain the profit as follows:

$$\pi_{it}(j) = P_{it}(1-\alpha) \alpha^{\frac{1+\alpha}{1-\alpha}} A_{it}(j) L_{it} \tag{12}$$

Let $\int_0^1 A_{it}(j) dj = A_{it}$, which denotes the average level of technological progress. Substituting equation (10) into equation (2), we obtain:

$$Y_{it} = \alpha^{\frac{2\alpha}{1-\alpha}} L_{it} \int_0^1 A_{it}(j) dj = \alpha^{\frac{2\alpha}{1-\alpha}} A_{it} L_{it} \tag{13}$$

Let the probability of successful R&D be τ_{it}. Then A_{it} can be expressed as:

$$A_{it} = \int_0^1 \gamma_i A_{it-1}(j) \tau_{it}(j)\, dj + \int_0^1 A_{it-1}(j)[1-\tau_{it}(j)] dj = \gamma_i A_{it-1} \tau_{it} + A_{it-1}(1-\tau_{it}) \tag{14}$$

According to the above equation, the technological progress growth rate of industry i, g_{it}, can be obtained as:

$$g_{it} = \frac{A_{it} - A_{it-1}}{A_{it-1}} = \frac{\gamma_i A_{it-1} \tau_{it} + A_{it-1}(1-\tau_{it}) - A_{it-1}}{A_{it-1}} = (\gamma_i - 1)\tau_{it} \tag{15}$$

The optimal innovation behavior of the R&D sector can be expressed as maximizing its R&D profit:

$$max. \tau_{it}(j) \pi_{it}(j) - P_{it} R_{it}(j) \tag{16}$$

Based on $\tau_{it}(j) = \lambda_i \left[\frac{R_{it}(j)}{L_{it} A_{it}^{*}(j)} \right]^{\frac{1}{2}}$, we obtain:

$$R_{it}(j) = L_{it} A_{it}^{*}(j) \left[\frac{\tau_{it}(j)}{\lambda_i} \right]^2 \tag{17}$$

The profit maximization problem of the R&D sector is equivalent to maximizing the probability of innovation success. Substituting the above expression into equation (16),

the optimal behavior of the R&D sector can be further expressed as:

$$max.\tau_{it}(j)P_{it}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}L_{it}A_{it}^{*}(j)-P_{it}A_{it}^{*}(j)\left[\frac{\tau_{it}(j)}{\lambda_i}\right]^2 L_{it} \quad (18)$$

Taking the first derivative and setting it equal to zero, we obtain:

$$\tau_{it}(j)=\frac{1}{2}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\lambda_i^2 \quad (19)$$

The above equation indicates that the success of innovation depends on the parameter α and the R&D efficiency λ_i. Therefore, the probability of successful innovation for different intermediate products in industry i is identical, that is, $\tau_{it}(j)=\tau_{it}$. Combining equations (4), (15), and (19), the technological innovation level of industry iii can be obtained as:

$$g_{it}=\frac{1}{2}(\gamma_i-1)(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\lambda_i^2=\frac{1}{2}(\gamma_i-1)(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\left(\theta Dig_{it}^{\beta_1}Mat_{it}^{\beta_2}\right)^2 \quad (20)$$

The most significant role played by the digital economy is to achieve efficient allocation of resources. On the one hand, with technological progress, technologies such as big data, cloud computing, and artificial intelligence have been increasingly applied across different industries. This enables firms to better utilize digital technologies to improve production efficiency, reduce costs, optimize management, and enhance user experience. On the other hand, with the deepening of digitalization, firms increasingly rely on data analysis to guide decision-making. Data has become an important asset that helps firms better understand market demand and consumer behavior. Therefore, as the digital economy develops, industries become more dependent on digital technologies and data resources to improve operational efficiency and competitiveness. Based on this reasoning, this paper assumes that the degree of matching between the digital economy and a given industry, Mat_{it}, is an increasing function of the level of digital economy development. That is, $\frac{\partial Mat_{it}}{\partial Dig_{it}}>0$.

Therefore, taking the first derivative of g_{it} with respect to Dig_{it}, we obtain:

$$\frac{\partial g_{it}}{\partial Dig_{it}}=(\gamma_i-1)(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\theta^2 Dig_{it}^{2\beta_1}Mat_{it}^{2\beta_2}\left(\frac{\beta_1}{Dig_{it}}+\frac{\beta_2}{Mat_{it}}\frac{\partial Mat_{it}}{\partial Dig_{it}}\right) \quad (21)$$

The above result indicates that the level of technological innovation in industry i depends on the output elasticity α. Given that $\gamma_i>1$, $0<\alpha<1$, $Dig_{it}>0$, $\frac{\partial Mat_{it}}{\partial Dig_{it}}>0$ and $\beta_1>0$, $\beta_2>0$, it follows that $\frac{\partial g_{it}}{\partial Dig_{it}}>0$.

This implies that the development of the digital economy promotes technological innovation. Based on the above analysis, this paper proposes the following hypotheses:

Hypothesis 1: The development of the digital economy significantly promotes the improvement of innovation levels.

Hypothesis 2: An increase in innovation levels significantly enhances the technological complexity of a country's export products, thereby improving its position in the international division of labor.

Hypothesis 3: The development of the digital economy promotes the technological complexity of export products by enhancing technological innovation.

4. Variable Selection and Data Sources

4.1. Dependent Variable

Drawing on the study of Xu Ye et al., this paper measures the quality of a country's export products using export technological complexity ($exp\,y_{it}$) [10]. The calculation is carried out in two steps. First, the technological complexity of export products is calculated as follows:

$$prod\,y_j=\sum_{i=1}^{n}\frac{x_{ij}/x_i}{\sum_{j=1}^{n}(x_{ij}/x_i)}Y_i \quad (22)$$

Based on the above equation, the export technological complexity of province i can be obtained as:

$$exp\;yit_i=\sum_{j=1}^{n}\left(\frac{x_{ij}}{x_j}\right)prod\,y_j \quad (23)$$

Following the approach of the United Nations Industrial Development Organization (UNIDO) in the Industrial Development Report 2016, this paper classifies export manufacturing industries into three categories—low-, medium-, and high-technology manufacturing—based on the statistical ratios of R&D intensity relative to value added and gross output. High-technology manufacturing mainly includes industries such as automobile manufacturing and computer and electronic manufacturing.

4.2. Key Explanatory Variable

Digital economy development level (Dgl). This paper constructs a digital economy indicator system, as shown in Table 1. The entropy method is then used to calculate the composite digital economy index.

First, all indicators are standardized as follows:

$$P_{ijt}=\frac{X_{ijt}-Min(X_{ijt})}{Max(X_{ijt})-Min(X_{ijt})} \quad (24)$$

Next, the weights and entropy values are calculated as follows:

$$Q_{ijt}=\frac{P_{ijt}}{\sum_{i=1}^{30}\sum_{t=2011}^{2021}P_{ijt}} \quad (25)$$

$$E_j=-k\sum_{i=1}^{30}\sum_{t=2011}^{2021}Q_{ijt}\,ln(Q_{ijt}) \quad (26)$$

To avoid computational errors when taking logarithms, 0.0001 is added to all obtained data. Then, the coefficient of variation for each indicator is calculated.

$$G_j=1-E_j \quad (27)$$

The weight of each indicator W_j is calculated as:

$$W_j=\frac{G_j}{\sum_{j=1}^{19}G_j} \quad (28)$$

Finally, the composite index of the digital economy is obtained, denoted as Dig_{it}.

$$Dig_{it}=100\times\sum_{j=1}^{19}W_jP_{ijt} \quad (29)$$

Dig_{it} represents the measured value of the digital economy development level for region i in year t, obtained using the entropy method.

In addition, during the robustness test, this paper recalculates the composite digital economy development index using principal component analysis (PCA). By replacing the explanatory variable with this alternative

measure, robustness checks are conducted. The procedure is as follows:

Step 1: To eliminate the influence of different variable scales, each variable is standardized so that it has unit variance.

$$Z = \frac{X-\mu}{\sigma} \tag{30}$$

Where μ denotes the mean of each variable and σ denotes the standard deviation.

Step 2: Compute the covariance matrix C of the standardized data matrix Z.

$$C = \frac{1}{n-1} Z^T Z \tag{31}$$

Step 3: Obtain the eigenvalues λ_i of the covariance matrix C and their corresponding eigenvectors v_i.

Step 4: Select the principal components. The eigenvalues are arranged in descending order, and the eigenvectors corresponding to the largest eigenvalues are selected as principal components. In this paper, the eigenvectors corresponding to the four largest eigenvalues are selected as the principal components.

Step 5: Data transformation. Project the original data onto these principal components to obtain the new dataset Y.

$$Y = Zv \tag{32}$$

Where v is the matrix composed of the selected eigenvectors.

Step 6: Interpretation and cumulative variance. The variance of each principal component is equal to its corresponding eigenvalue. The cumulative explained variance of the principal components provides a trade-off between the number of retained principal components and the amount of information contained in the original data.

Step 7: Construction of the composite index. The principal components are weighted according to their variance contributions and then aggregated to obtain the composite score, which represents the new measure of digital economy development level.

$$Pca = \sum_{k=1}^{4} \lambda_k Y_k \tag{33}$$

Where Y_k denotes the score of the $k-th$ principal component, and λ_k denotes the eigenvalue of the $k-th$ principal component.

Table 1. Indicator System for the Composite Development Level of the Digital Economy in Chinese Cities

Target Layer	Primary Indicators	Secondary Indicators	Indicator Description	Attribute
Digital Economy Development Indicators	Digital Economy Infrastructure	Mobile phone penetration	Number of mobile phone subscribers per 100 people	+
		Internet penetration	Proportion of Internet users in the permanent population (%)	+
		Information transmission capacity	Optical cable line density (km/km²)	+
		Signal coverage capacity	Density of mobile phone base stations (per km²)	+
		Internet broadband infrastructure	Density of Internet broadband access ports (per km²)	+
		Investment in digital services	Per capita fixed asset investment in information transmission, computer services and software industry (yuan/person)	+
	Digital Industrialization	Development level of postal and telecommunications industry	Per capita telecommunication business volume (yuan/person)	+
			Per capita postal business volume (yuan/person)	+
			Express delivery volume (10,000 parcels)	+
		Development level of electronic information manufacturing	Revenue of electronic information manufacturing industry (10,000 yuan)	+
			Number of electronic information manufacturing enterprises	+
		Software and information technology service industry	Software business revenue (10,000 yuan)	+
			Number of employees in information transmission, software and IT services (10,000 persons)	+
	Industrial Digitalization	Enterprise digital development level	Number of enterprise websites	+
			Proportion of enterprises engaged in e-commerce transactions (%)	+
			E-commerce transaction volume (100 million yuan)	+
		Development level of digital inclusive finance	Digital financial coverage index	+
			Digital financial usage depth index	+
			Digital financial digitization level	+

4.3. Mediating Variable

The mediating variable selected in this paper is the level of technological innovation ($innovation$), which is measured by the ratio of government expenditure on science and technology to general public budget expenditure.

4.4. Control Variables

Drawing on the existing literature, this paper includes the following control variables: trade openness, level of

economic development, industrial structure, and population density.

Table 2. Descriptive Statistics of Variables

Variable	Minimum	Mean	Maximum	Standard Deviation	Observations
$exp\,y_{it}$	2.5420	5.5018	8.8866	1.2045	330
Dgl	0.0096	0.1188	0.6465	0.1084	330
$opening$	0.0076	0.2653	1.5482	0.2908	330
$density_population$	7.8638	473.3073	3925.87	704.8451	330
$industrial_structure$	0.5180	1.2456	5.2968	0.7046	330
$economic_development$	9.7073	10.8711	12.1227	0.4451	330

Trade openness ($opening$). On the one hand, trade openness promotes international technological exchange and cooperation, enabling domestic firms to acquire advanced technologies and managerial experience more easily. On the other hand, trade openness allows firms to take advantage of advanced technologies and high-quality resources within global supply chains, thereby improving production efficiency and product quality. Both channels contribute to the export of products with higher technological content. The variable is measured as follows: $opening = \frac{Total\ imports\ and\ exports}{Real\ GDP}$.

Economic development level ($economic_development$). First, economically developed regions usually possess sufficient capital accumulation, enabling firms to undertake large-scale R&D and technological investments. Higher levels of investment support firms in developing high value-added products and facilitate their entry into international markets. Second, more developed regions tend to cultivate a large number of highly skilled technical professionals, who play a crucial role in R&D and the production of high-tech products, thereby promoting the transformation of export manufacturing toward higher technological levels.

Industrial structure ($industrial_structure$). A higher share of technology-intensive industries implies that the region possesses stronger R&D capabilities and production capacity in high-tech sectors. Consequently, export products from such industries tend to embody higher technological value added.

Population density ($density_population$). Regions with higher population density are often characterized by the concentration of higher education institutions and research organizations, which helps cultivate a large pool of high-quality human capital. Since high-tech export manufacturing relies heavily on specialized technical personnel and researchers, regions with higher population density are more likely to generate talent agglomeration effects, thereby promoting technological innovation and the development of high-tech products.

Data Sources and Descriptive Statistics. Due to the severe data deficiencies in the Tibet Autonomous Region and the limited availability of certain indicators, such as the Digital Financial Inclusion Index, this study sets the sample period from 2011 to 2021. The Tibet Autonomous Region as well as Hong Kong, Macao, and Taiwan are excluded from the sample. After filling a small number of missing observations using linear interpolation, the final dataset consists of panel data from 30 provinces in China, with a total of 330 observations. The data are obtained from several sources, including the China Statistical Yearbook, China Information Industry Yearbook, Statistical Yearbook of the Ministry of Industry and Information Technology of the People's Republic of China, China Electronic Information Industry Statistical Yearbook, China Tertiary Industry Statistical Yearbook, the Digital Finance Research Center of Peking University, as well as provincial statistical yearbooks and statistical bulletins. The descriptive statistics of the variables are reported in Table 2.

5. Empirical Results Analysis

5.1. Baseline Regression Results

The baseline regression model is specified as follows:

$$exp\ yit_{it} = \alpha_0 + \eta_1 Dgl_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (34)$$

As shown in Table 3, during the process of gradually introducing control variables, the coefficient of the core explanatory variable ^{Dgl} remains significantly positive at the 1% significance level, indicating a positive relationship between the development of the digital economy and the technological complexity of export products. Column (1) reports the regression results without control variables, while columns (2)–(5) present the results after sequentially adding control variables, including trade openness, population density, government intervention, economic development level, and industrial structure.

Table 3. Baseline Regression Results: The Impact of the Digital Economy on the Technological Complexity of Export Products

Variables	$exp\ y\ it_{it}$				
	(1)	(2)	(3)	(4)	(5)
Dgl	15.5753*** (0.6961)	18.5138*** (0.8561)	20.3019*** (0.9684)	8.2865*** (0.9576)	4.9321*** (0.8375)
$opening$		3.3569*** (0.6160)	2.0847*** (0.6949)	-0.7631 (0.4907)	1.9941*** (0.4171)
$density_population$			-0.0136*** (0.0037)	-0.0097*** (0.0026)	-0.0034 (0.0022)
$economic_development$				-3.2733*** (0.1848)	-2.5194*** (0.1649)
$industrial_structure$					1.4178*** (0.1192)
$cons_$	3.6520*** (0.0920)	2.4120*** (0.2439)	8.9917*** (1.7985)	44.5004*** (2.3653)	31.6292*** (2.2282)
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.6261	0.6600	0.6749	0.8422	0.8933
N	330	330	330	330	330

Note: *p < 0.1, **p < 0.05, **p < 0.01. Standard errors are reported in parentheses.

5.2. Robustness Tests of the Baseline Regression

To ensure the robustness of the empirical results, this study adopts three methods for robustness tests.

(1) Principal Component Analysis (PCA) is used to replace the digital economy development index calculated by the entropy method. The technological complexity of export products is then re-estimated using the following regression model:

$$exp\ y\ it_{it} = \alpha_0 + \eta_1 pca_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (35)$$

(2) Since the impact of the digital economy on high-tech export manufacturing firms may exhibit a time-lag effect, this study uses the first-order lagged terms of the digital economy index calculated by both the entropy method and principal component analysis (PCA) as explanatory variables to further test the robustness of the model. The regression equations are specified as follows:

$$exp\ y\ it_{it} = \alpha_0 + \eta_1 L.Dgl_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (36)$$

$$exp\ y\ it_{it} = \alpha_0 + \eta_1 L.pca_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (37)$$

It can be observed that after conducting three robustness checks—replacing the explanatory variable Dgl with PCA, introducing the one-period lagged digital economy index calculated by the entropy method, and introducing the one-period lagged digital economy index constructed using principal component analysis (PCA)—the regression results remain significantly positive. This indicates that the development of the digital economy indeed promotes the production of export products with higher technological complexity.

Table 4. Robustness Tests of the Impact of the Digital Economy on the Technological Complexity of Export Products

Variables	Baseline Regression	Lagged Dgl	PCA Replacement	Lagged PCA
Dgl	4.9321*** (0.8375)			
$L.Dgl$		5.3604*** (0.9173)		
pca			0.5791*** (0.0374)	
$L.pca$				0.5824*** (0.0407)
$cons_$	31.6292*** (2.2282)	28.6392*** (2.6279)	19.0057*** (1.9790)	15.6968*** (2.3486)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.8933	0.8814	0.9342	0.9242
N	330	300	330	300

Note: *p < 0.1, **p < 0.05, **p < 0.01. Standard errors are reported in parentheses.

5.3. Mechanism Analysis

The previous theoretical analysis suggests that improvements in the level of digital economy development can promote technological innovation, which in turn enables export manufacturers to produce products with higher technological complexity. To verify this transmission mechanism, and following the research approach of Ye Kangtao (2018), this study constructs a mechanism testing model as follows:

$$exp\ y\ it_{it} = \alpha_0 + \eta_1 Dgl_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (38)$$

$$innovation_{it} = \alpha_0 + \eta_1 Dgl_{it} + \eta_2 Z_{it} + \varepsilon_{it} \quad (39)$$

$$exp\ yit_{it} = \alpha_0 + \alpha_1 Dgl_{it} + \alpha_2 innovation + \alpha_3 Z_{it} + \varepsilon_{it} \quad (40)$$

If the regression coefficients α_1 α_2 and α_3 are all statistically significant, it indicates that the mediating variable innovation can enhance the impact of the digital economy on the technological complexity of export products. The above models are then estimated using the stepwise regression method, and the results are reported in Table 5. The conclusions are as follows:

Column (1) reports the linear regression results of the digital economy on the technological complexity of export products, indicating that the development of the digital economy can significantly promote the technological complexity of export products.

Column (2) presents the regression results of the digital economy on the level of innovation, showing that the development of the digital economy significantly promotes the improvement of innovation capacity, which is consistent with the results derived from our theoretical analysis.

Column (3) reports the regression results of innovation on the technological complexity of export products, indicating that improvements in innovation capability contribute to the increase in the technological complexity of export products.

Column (4) includes both the digital economy and innovation as explanatory variables in the regression of export product technological complexity. The results show that both the digital economy and innovation remain significantly positive at the 1% significance level, suggesting that they both play a promoting role. Meanwhile, by comparing columns (1) and (3), it can be observed that the absolute value of the coefficient in column (4) is smaller than that obtained in the regressions where export technological complexity is explained by each variable separately. This indicates that innovation plays a positive mediating role in the process through which the digital economy enhances the technological complexity of export products.

Table 5. Mechanism Test of the Impact of the Digital Economy on the Technological Complexity of Export Products

Variables	(1)	(2)	(3)	(4)
Dgl	4.9321*** (0.8375)	2.0131*** (0.4650)		4.0129*** (0.8369)
$innovation$			0.5757*** (0.1021)	0.4567*** (0.1016)
$cons_$	31.6292*** (2.2282)	27.0887*** (1.2373)	18.1184*** (3.6176)	19.2597*** (3.4980)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.8933	0.7566	0.8924	0.9002
Observation	330	330	330	330

Note: *p < 0.1, **p < 0.05, **p < 0.01. Standard errors are reported in parentheses.

5.4. Heterogeneity Analysis

Due to differences in resource endowments, policy environments, and market development, the levels of development across Chinese cities exhibit considerable regional disparities. To further examine the heterogeneous effects of digital economy development on the mediating role of innovation in shaping export technological complexity across different regions, this study classifies the 30 provinces into three groups based on their geographical locations: eastern, central, and western regions.

First, descriptive statistics of export technological complexity, technological innovation, and the digital economy index are presented for provinces with different regional characteristics. The results are reported in Table 6.

Table 6. Regional Differences in Export Technological Complexity, Innovation, and Digital Economy Development across Provinces

Variable	Region	Maximum	Minimum	Mean	Standard Deviation	Observation
$exp\ y\ it$	Eastern	8.8866	3.6584	5.7386	1.1807	110
	Central	7.4930	3.4672	5.5273	1.1452	66
	Western	7.5800	2.5420	5.3218	1.2232	154
$innovation$	Eastern	16.2829	11.4959	14.2859	1.0870	110
	Central	15.2397	12.2700	13.8627	0.7548	66
	Western	14.8203	10.5348	12.9023	1.2232	154
Dgl	Eastern	0.6465	0.1968	0.2112	0.1395	110
	Central	0.1670	0.0181	0.0838	0.0411	66
	Western	0.1778	0.0096	0.0678	0.0370	154

It can be observed that the levels of digital economy development, innovation capability, and export technological complexity decrease sequentially from the eastern, central, to the western regions. This pattern can be attributed to the fact that the eastern region possesses the most developed economic foundations and industrial structures in China. These regions started economic development earlier and have accumulated substantial capital, technological capabilities, and managerial experience. In addition, advanced manufacturing and high-tech industries occupy an important

position in the eastern region, making significant contributions to the technological complexity of export products. Furthermore, the eastern region benefits from well-developed internet infrastructure and the widespread application of information and communication technologies (ICT). Major internet companies such as Alibaba, Tencent, and Baidu are headquartered in the eastern region, which has further promoted the rapid development of the regional digital economy. Finally, the eastern region is endowed with abundant scientific research institutions and higher education resources, including numerous key universities and research institutes. Governments and enterprises in these regions also invest more in research and development (R&D), attracting a large number of highly skilled talents and innovative projects. By contrast, the central and western regions lag behind the eastern region in the above aspects.

The results of the regional heterogeneity test reported in Table 7 show that the digital economy has a significantly positive effect on urban export technological complexity across all regions. Among them, the impact of the digital economy on export technological complexity is strongest in the central region, followed by the western region, while the effect is relatively smaller in the eastern region. This pattern may be explained by the fact that the eastern region has already reached a relatively mature stage of development, where the marginal effect of the digital economy is relatively limited. In contrast, the central region is currently undergoing rapid economic development, and thus the marginal effect of digital economy development is more pronounced. Meanwhile, the relatively weaker effect observed in the western region may be related to the less developed digital infrastructure compared with that in the central and eastern regions.

Table 7. Regional Heterogeneity Test Results of the Impact of the Digital Economy on Urban Export Technological Complexity

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Eastern Region		Central Region		Western Region	
Dgl	3.2418*** (0.9755)	1.8235** (0.8764)	14.1926*** (3.6777)	15.1298*** (1.1634)	12.7470*** (2.5146)	10.2267*** (2.7551)
$innovation$		0.9922*** (0.1711)		-0.0967 (0.2051)		0.4014** (0.1901)
$cons_$	34.6976*** (4.9801)	11.7979** (5.8362)	33.8860*** (5.8529)	36.6705*** (8.3430)	26.3451*** (4.0914)	19.5312*** (5.1708)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.9045	0.9296	0.9524	0.9526	0.8854	0.8891
Observation	110	110	66	66	154	154

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are reported in parentheses. Columns (1), (3), and (5) present regression results without the mediating variable, while columns (2), (4), and (6) include the mediating variable innovation.

6. Further Analysis

Compared with traditional econometric regression methods, machine learning exhibits distinct advantages in handling nonlinear relationships, high-dimensional data, and improving predictive accuracy. Econometric analysis typically focuses on explaining why a phenomenon occurs, with its primary objective being causal inference—that is, identifying and verifying the causal relationships implied by theoretical models using economic data. Methodologically, econometrics usually relies on probabilistic statistical frameworks, such as large-sample asymptotic theory and Monte Carlo simulations for small samples. These approaches generally require relatively strong assumptions. Although they possess strong explanatory power, their predictive performance is often limited and may deviate from real-world outcomes. In contrast, machine learning mainly addresses the question of what will happen in the future, with the primary objective of improving the closeness between predicted values and actual observations. From a methodological perspective, machine learning is largely based on optimization techniques, which typically involve minimizing a specific objective function. Compared with traditional econometric regression models, machine learning methods are capable of automatically capturing complex nonlinear relationships, handling high-dimensional and heterogeneous data structures, and performing automated feature selection and feature engineering, thereby improving predictive performance. The relationship between the digital economy and export technological complexity may exhibit strong nonlinear characteristics. Therefore, it is necessary to employ machine learning methods, such as the random forest model, for regression analysis. The random forest model does not require a pre-specified functional form and can automatically capture complex nonlinear relationships within the data. In addition, random forests provide measures of variable importance during the variable selection process, which helps identify the key factors that have the greatest impact on export technological complexity. Based on these advantages, this paper employs the random forest model to further examine the relationship between the digital economy and export technological complexity.

6.1. Model Selection

Machine learning regression models commonly include decision trees, support vector machines, gradient boosting regression trees, and random forest models. Due to differences in data-generating processes, the performance of different models may vary. Common indicators used for model selection include the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean squared error (MSE). A higher value of R^2 indicates better predictive performance of the model, while lower values of RMSE, MSE, and MAE indicate smaller prediction errors and thus better model accuracy.

Table 8. Comparison of Predictive Performance across Different Regression Models

Model	R^2	RMSE	MSE	MAE
Random Forest	0.9146	0.3739	0.1398	0.2974
Decision Tree	0.7966	0.5770	0.3329	0.4423
Gradient Boosting Regression Tree	0.9427	0.3062	0.0937	0.2482
Support Vector Machine	0.7077	0.6917	0.4784	0.5802

In summary, the gradient boosting regression tree and random forest models perform better on the test set, both effectively explaining the variation in the data while producing relatively small prediction errors. Considering that the random forest model provides greater interpretability, this study ultimately selects the random forest model for regression analysis.

6.2. Model Training and Optimization

The training and optimization of the random forest model constitute a key part of this study. To ensure the accuracy and reliability of the model, a regression tree framework is adopted and hyperparameters are optimized using the grid search method. The specific procedures are as follows.

First, data preprocessing. The data are first encoded to ensure that the model can correctly recognize and process categorical variables. Subsequently, the dataset is divided into a training set and a test set for subsequent model training and evaluation.

Second, hyperparameter setting. The random forest regression model contains several hyperparameters that need to be tuned, including the number of trees ($n_estimators$), the maximum depth of the trees (max_depth), and the maximum number of features considered at each split ($max_features$). A parameter grid ($param_grid$) is constructed to define the search range for these hyperparameters.

Third, grid search with cross-validation. To determine the optimal hyperparameter combination, this study adopts a grid search method combined with cross-validation. Using the GridSearchCV function, cross-validation is performed for each hyperparameter combination, and the best parameter set is selected according to the R^2 score. Each cross-validation process uses five folds to ensure the stability and reliability of the results.

Fourth, selection of the optimal feature number ($max_features$). This study further examines the effect of different $max_features$ values on model performance. By iterating over different $max_features$ values, the corresponding best R^2 score for each value is recorded. The value that yields the best performance is finally selected and used to train the final model.

6.3. Results and Analysis

Feature Importance Ranking. The figure below presents the relative importance of feature variables affecting export technological complexity. It can be observed that the digital economy (Dgl) has the greatest impact on export technological complexity. Although the level of innovation ranks last, it still exerts a significant influence on export technological complexity. Based on the feature importance results, it can be inferred that regions with relatively lower levels of digital economic development, particularly the central and western regions, should accelerate the development of the digital economy. Specific measures may include promoting comprehensive 5G network coverage, especially in central, western, and rural areas, in order to reduce the digital divide between eastern and central–western regions.

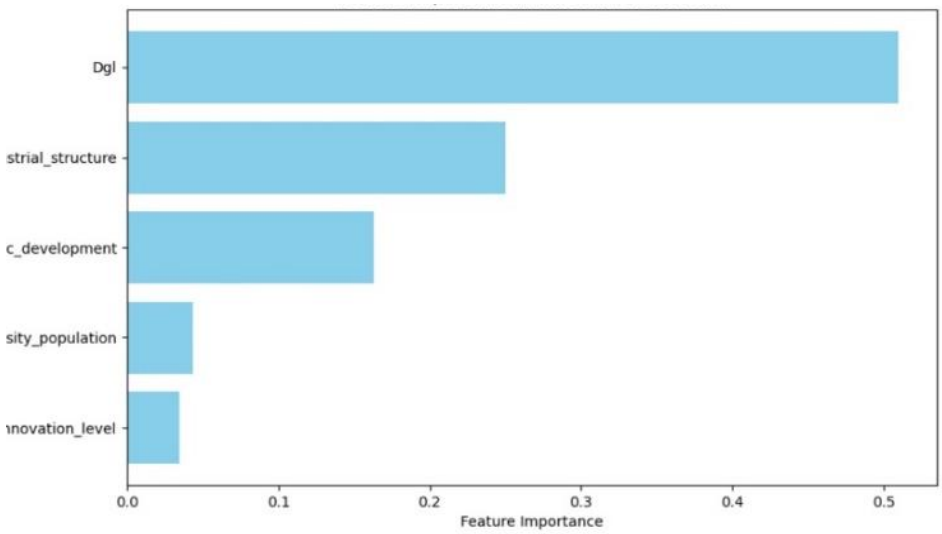


Figure 1. Relative Importance of Feature Variables

Selection of the Optimal Feature Number. This study employs a grid search method combined with cross-validation to determine the optimal parameters. Specifically, the GridSearchCV function is used to conduct predictions on the test set, and the optimal parameter combination is selected based on the R2 score. The results show that when $max_features = 7$, the model achieves the highest score on the test set and demonstrates the best predictive performance. Therefore, this study selects the corresponding number of feature variables to train the random forest model.

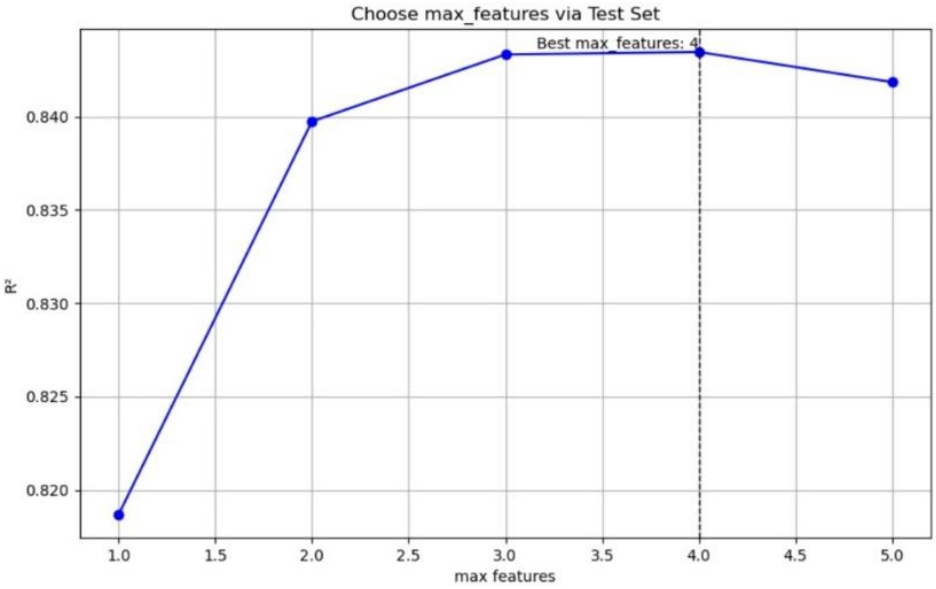


Figure 2. Cross-Validation Results

Partial Dependence Plot. The Partial Dependence Plot (PDP) is a method used to interpret the output of machine learning models, illustrating the marginal effect of one or more features on the target variable. By fixing all other features except the target feature, the partial dependence plot examines how changes in the selected feature influence the prediction results. As shown in Figure 3, the digital economy has a significant positive effect on export technological complexity.

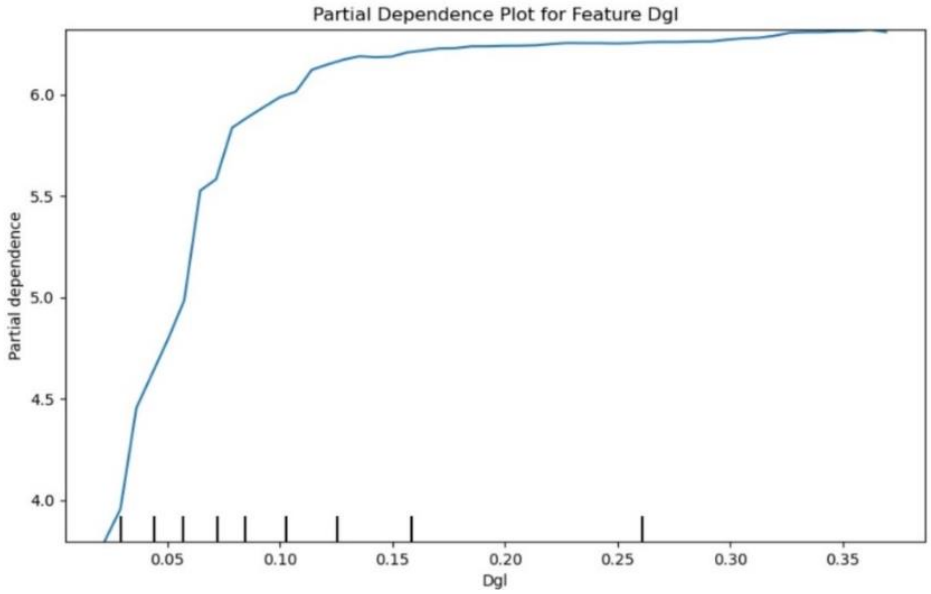


Figure 3. Partial Dependence Plot of the Digital Economy on Export Technological Complexity

Partial Dependence Plot and Decision Tree Model. Figure 4 presents a decision tree with a depth of 3 derived from the random forest regression model. The decision tree further verifies the analysis proposed in the theoretical framework, showing that the digital economy and technological innovation play a leading role in determining export technological complexity. At the same time, the results provide additional evidence that the digital economy promotes the improvement of export technological complexity by enhancing the level of technological innovation.

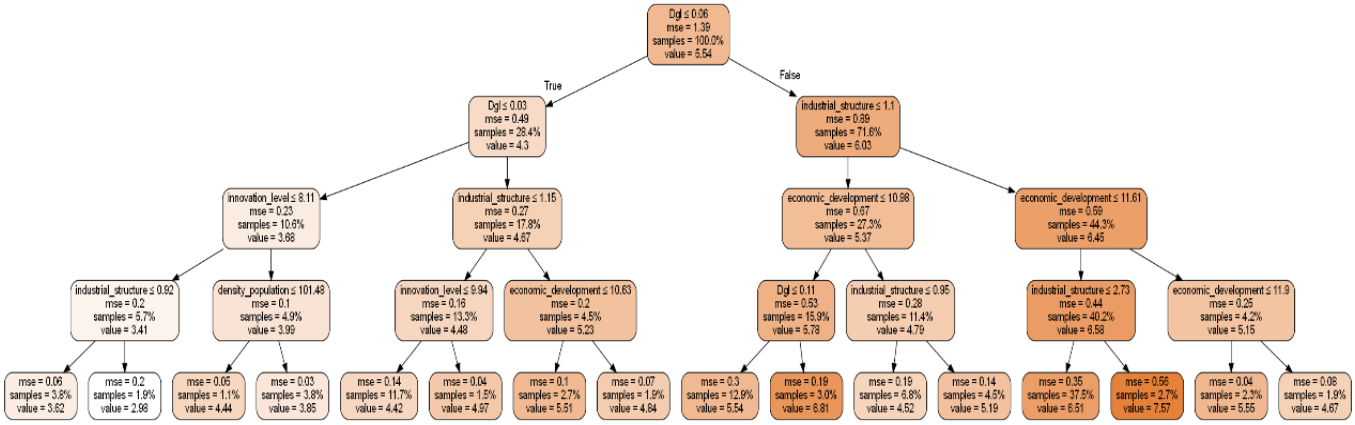


Figure 4. Decision Tree Model of the Digital Economy and Export Technological Complexity

7. Conclusions and Implications

The long-standing development model of improving export technological complexity primarily through the introduction of advanced capital equipment has, to some extent, overlooked the importance of independent innovation and research and development, thereby constraining firms' innovation capacity and the overall quality of economic development. Under the new development paradigm and the construction of a unified national market, promoting high-quality export development through the development of the digital economy and innovation pathways deserves further attention.

Based on the construction of a provincial-level digital economy development index and panel data from 30 Chinese provinces during 2011–2022, this study empirically examines the impact of digital economy development on export technological complexity. The main conclusions are as follows.

First, the development of the digital economy significantly promotes high-quality export growth and improves China's position in international trade. This conclusion remains robust after various robustness checks, including replacing explanatory variables and introducing lagged terms of the digital economy index.

Second, mechanism analysis shows that the digital economy improves the technological complexity of export products by enhancing the level of technological innovation. From this perspective, for a country to achieve long-term development, it must address the technological barriers of innovative countries in international trade by strengthening its own innovation capabilities.

Third, heterogeneity analysis indicates that the positive impact of the digital economy on export technological complexity is more significant in the eastern region, while the transformation effect of innovation outcomes in the central region remains relatively weak. In addition, the digital infrastructure in the western region is still relatively underdeveloped.

Based on the above conclusions, the policy implications of this study can be summarized in three aspects.

First, efforts should be made to promote the construction of digital economy infrastructure, particularly big data algorithms and cloud service platforms. By accelerating the deployment of 5G networks and optical broadband, high-speed and stable network support can be provided for big data and cloud computing. In addition, fiscal subsidies, tax incentives, and R&D funding support should be provided to encourage enterprises and research institutions to develop advanced big data algorithms and analytical tools, thereby enhancing data processing and analysis capabilities. At the same time, the development of cloud computing services should be promoted to support enterprises in adopting cloud service platforms, such as Alibaba Cloud, thereby improving data storage, computing, and analytical capacities while reducing the costs and barriers of digital transformation for firms.

Second, technological innovation support should be strengthened to enhance independent R&D capabilities. This includes promoting industry–university–research collaboration, strengthening cooperation among universities, research institutes, and enterprises, establishing joint R&D centers and innovation laboratories, jointly tackling key technological challenges, and accelerating the transformation of scientific and technological achievements. In addition, greater support should be provided to key technological fields such as artificial intelligence, blockchain, and the Internet of Things, thereby promoting China's international competitiveness in these areas and enhancing its competitiveness in global trade.

Third, in accordance with the 14th Five-Year Plan for Digital Economy Development and the Guiding Opinions on Accelerating the Construction of a Manufacturing Power, differentiated policies should be implemented to promote both digital industrialization and industrial digitalization. Given that the transformation effect of innovation outcomes in the central region remains relatively weak, the government should increase policy support for this region and optimize the allocation of regional innovation resources. Specific measures may include establishing regional innovation funds to support scientific and technological innovation projects in the central region. Through policy guidance and resource support, the efficiency of innovation outcome transformation in the central region can be improved, thereby promoting high-quality regional economic development.

Through the implementation of these policy measures, China can further promote the development of the digital economy, enhance technological innovation capabilities and the technological complexity of export products, strengthen international competitiveness, and ultimately promote high-quality development in international trade.

References

[1] Dai Chu, Huang Ying, Wang Siyi. Innovative city policies, factor market integration, and export technological complexity [J]. International Trade Issues, 2023(12):114–131.

[2] Lu Xiuxiu, Fang Hangming, Zhang Anquan. Digital economy, spatial spillovers, and high-quality urban economic development [J]. Economic Review, 2021, 38(06):21–31.

[3] Yang Xianming, Zhang Shengli, Li Bo. Participation in dual value chains and China's export technological upgrading: Evidence from manufacturing sector data [J]. World Economic Research, 2023(12):13–27+132. DOI:10.13516/j.cnki.wes.2023.12.006.

[4] Chen Jianbin. Review of the development of international trade theory [J]. Shanghai Journal of Economics, 2004(12):68–70+67.

[5] Stern R. M., Maskus K. E. Determinants of the structure of U.S. foreign trade, 1958–1976 [J]. Journal of International Economics, 1981, 11(2):207–224.

[6] Wakelin K. The role of innovation in bilateral OECD trade performance [J]. Applied Economics, 1998, 30(10):1335–1346.

[7] Yao Limin, Fang Rongdong. Technological innovation and China's export trade: An empirical study [J]. International Business Research, 2007(03):12–17.

[8] Li Ping. On the relationship between international trade and technological innovation [J]. World Economy Study, 2002(05):79–83+89.

[9] Yu Zengsheng. Empirical study on the relationship between technological innovation and export trade [J]. Scientific Research Management, 2011, 29(02):300–305.

[10] Xu Wei, Zhu Yu, Wang Changqi. Intelligent manufacturing, labor skill structure, and export technological complexity [J]. Financial Research, 2022, 33(03):16–27.

[11] Yin Hua, Liu Yanfeng. Business environment and provincial export technological complexity in manufacturing: Evidence from mediation analysis based on panel data from 31 provinces [J]. Journal of Henan Normal University (Philosophy and Social Sciences Edition), 2022, 49(02):84–92.

[12] Bai Xueqing, Song Zhi, Li Lin. Can the digital economy promote China's industrial structure upgrading? Evidence from the perspective of efficiency and technological progress [J]. Journal of Xi'an Jiaotong University (Social Sciences), 2021, 41(06):1–15.

[13] Yi Xin, Liu Fengmin. Financial development, technological innovation, and industrial structural transformation: A multi-sector endogenous growth theoretical framework [J]. Management World, 2015(10):24–39+90.

[14] Ye Kangtao, Liu Fang, Li Fan. Equity incentive adjustment and stock price crash risk: Evidence from a natural experiment [J]. Journal of Financial Research, 2018(03):172–189.

[15] Tao Meijing, Jian Chunshu. International trade, technological innovation, and the skill wage gap in China's cities: Evidence from microdata of labor individuals [J]. International Trade Issues, 2016(05):16–27.

[16] Wen Jun, Liu Hong, Zhang Sen. Digital trade and the elimination, reconstruction, and response to international trade barriers [J]. International Trade, 2023(02):64–71.