Research on the Impact of Digital Inclusive Finance on the Technological Complexity of Enterprises' Exports

Yuhan Hou *

School of Economics, Northeastern University, Qinhuangdao 066003, China

* Corresponding Author Email: 3153611761@qq.com

Abstract. This paper explores the impact of digital inclusive finance on the technological complexity of enterprises' export products and its underlying mechanisms. Based on data from Chinese A-share listed companies between 2012 and 2016, the study finds that digital inclusive finance significantly enhances the technological complexity of export products by optimizing resource allocation, strengthening innovation incentives, and improving information efficiency. Heterogeneity analysis reveals that digital inclusive finance has a more pronounced effect on upgrading export technological complexity in western regions, non-state-owned enterprises, and enterprises with integrated chairman and general manager positions. Mechanism analysis further confirms that optimized resource allocation, innovation incentives, and improved information efficiency are critical pathways through which digital inclusive finance influences the technological complexity of enterprises' export products.

Keywords: Digital Inclusive Finance, Technological Complexity of Export Products, Resource Allocation, Innovation Incentives, Information Efficiency.

1. Introduction

China's economy is undergoing a transformation from "scale expansion" to "quality improvement," with the foreign trade sector facing an urgent need for high-quality development. According to data from the General Administration of Customs, the unqualified rate of China's export products remained at 3.2% in 2023, with the lag in technological upgrading of small and medium-sized enterprises (SMEs) due to financing constraints identified as a core bottleneck (Xie Xuanli, 2018). Meanwhile, digital inclusive finance—through innovative models such as big data risk control and supply chain finance—has covered over 30 million SMEs. Its potential in optimizing resource allocation and reducing information costs (Pan Tong et al., 2024; Li Hua, 2024) offers a new pathway to address the export quality dilemma.

From a policy perspective, the *14th Five-Year Plan for Digital Economy Development* explicitly requires "leveraging the enabling role of digital finance in the real economy." Additionally, the global market’s demand for green and intelligent products—such as the EU’s *New Battery Regulations* covering 80% of electronic product exports—forces enterprises to enhance quality competitiveness through technological innovation. Against this backdrop, exploring how digital inclusive finance influences the technological complexity of enterprises’ export products is of significant practical importance for promoting foreign trade transformation and upgrading.

Existing literature has preliminarily revealed the incentive effects of digital inclusive finance on enterprise innovation (Liu Guiping, 2020; Wang Yuewu & Zhang Yu, 2023), but its impact mechanisms on export technological complexity remain unclear. First, the resource allocation effect is questionable: while digital finance can alleviate financing constraints (Pan Tong et al., 2024), whether funds are prioritized for quality upgrading (e.g., testing equipment investment, technological R&D) requires verification. Second, the information efficiency transmission pathway is ambiguous: there is no systematic conclusion on whether digital technologies can significantly reduce enterprises’ costs of acquiring international market demand and optimize product design. Third, research on industry heterogeneity is insufficient: existing studies mainly focus on traditional manufacturing industries (e.g., textiles, agricultural products), lacking analysis of quality upgrading paths in emerging industries such as new energy vehicles and biomedicine.

Digital inclusive finance empowers the upgrading of export technological complexity through two pathways: resource allocation optimization and information efficiency improvement. On one hand, relying on big data risk control and supply chain finance models, it accurately matches SMEs' funding needs for technological upgrading, alleviating traditional financing constraints on testing equipment investment and green technology R&D (Pan Tong et al., 2024), and directly boosting export product qualification rates. For example, photovoltaic enterprises using digital finance to procure intelligent testing equipment reduced their product unqualified rate from 5% to 1.8%. On the other hand, digital technologies lower enterprises' information costs for accessing international market demand—such as analyzing target-country consumer preferences via Google Trends data to optimize product function design (Wang Handi et al., 2022)—increasing quality upgrading indices in emerging industries (e.g., lithium batteries) by an average of 12%. Moreover, digital finance has a more pronounced enabling effect on emerging industries, as funds are more likely to flow into green technology areas like carbon footprint tracking and intelligent testing, aligning with global market demands for intelligent and low-carbon products (e.g., the EU's *New Battery Regulations*).

However, the expansion of digital inclusive finance may trigger resource misallocation risks and technological path dependence, thereby inhibiting export technological complexity. On one hand, some enterprises may use digital finance funds for short-term scale expansion rather than quality upgrading. In traditional manufacturing, for instance, textile enterprises overly reliant on inclusive loans to expand production capacity may neglect investments in fabric environmental testing equipment, leading to delayed improvements in export qualification rates (Xie Xuanli, 2018). On the other hand, highly digitized enterprises may form "data dependence," excessively focusing on existing market demand data (e.g., e-commerce platform reviews), which could suppress breakthrough technological innovation and trap quality upgrading in emerging industries like biomedicine at the imitation level, failing to overcome international high-end standard barriers. Additionally, industry heterogeneity may exacerbate negative effects: traditional labor-intensive enterprises with insufficient digital capabilities may fall into "low-quality involution" with digital finance support, while small and medium-sized enterprises lacking professional risk control teams may compromise R&D investment sustainability due to overborrowing, indirectly hindering quality upgrading.

Therefore, this study empirically examines the relationship between digital inclusive finance and export technological complexity. Using a sample of Chinese A-share listed companies from 2012 to 2016, we employ a two-way fixed-effects model to verify the positive impact of digital inclusive finance on export technological complexity, followed by robustness tests, heterogeneity analysis, and mechanism analysis to validate the conclusions. The structure is as follows: Chapter 2 reviews the literature; Chapter 3 presents research hypotheses; Chapter 4 describes the empirical design; Chapter 5 reports empirical results; Chapter 6 conducts further analysis, including heterogeneity and mechanism analyses; and Chapter 7 concludes with policy recommendations.

2. Literature Review

2.1. Research on Digital Inclusive Finance.

As an emerging concept in the financial sector, digital inclusive finance has garnered extensive attention in recent years. By leveraging digital technologies, it breaks through the limitations of traditional finance to extend financial services to broader groups, particularly small and medium-sized enterprises (SMEs) and vulnerable populations, thereby promoting financial equity and accessibility.

In terms of resource allocation efficiency, Pan Tong et al. (2024) analyzed the impact of digital finance on resource allocation in SMEs using data from Alibaba International Station's export transactions (2018–2022), digital financing records of Wangshang Bank, and customs export quality inspection data. They found that digital finance significantly increased the qualification rate of SMEs' export products by 5%–8% through the pathway of "alleviating financing constraints → increasing

productive investment → improving product quality." The integration of cross-border e-commerce platforms with digital financing tools (e.g., Wangshang Bank's "310" model) has drastically reduced financing costs, supporting enterprise equipment upgrades and technological transformations to optimize resource allocation. Li Hua (2024) combined the Peking University Digital Inclusive Finance Index (2016–2021), China Customs' agricultural export quality monitoring data, and agricultural enterprise surveys to empirically study digital inclusive finance's role in agriculture. Results showed that it improved agricultural export quality indices by 0.2–0.4 percentage points via "optimizing capital allocation → enhancing agricultural technology and equipment," demonstrating its effectiveness in optimizing resource allocation and productivity in agriculture. Yin Zhichao et al. (2020) used China Household Finance Survey data to find that digital inclusive finance has a more pronounced resource allocation effect on rural SMEs, alleviating their "financing difficulties and high costs" and driving technological equipment upgrades. Zhang Yilin et al. (2022) analyzed Sci-Tech Innovation Board enterprises and found that digital finance increased R&D equipment investment in high-tech firms by 15% through "precise risk control → targeted capital allocation," outperforming traditional financial channels.

In innovation incentives, Liu Guiping (2020) studied digital inclusive finance's impact on SME innovation using data from the People's Bank of China's inclusive finance targeted reserve requirement reductions (2017–2020), NEEQ financial reports, and patent application data. He found that it increased SMEs' R&D intensity by 0.3–0.5 percentage points and patent applications by 12% via "alleviating financing constraints → increasing R&D investment → enhancing product technology content." Big data risk control and supply chain finance platforms reduced credit risk assessment costs and improved industrial chain capital efficiency, fostering an enabling environment for innovation. Wang Yuewu and Zhang Yu (2023) used data from the National Bureau of Statistics' China Industrial Enterprise Database, Wind, and CNIPA patent classifications to further confirm that digital inclusive finance increased SME patent applications by 12% (with an 8% rise in invention patents) through "financial support + risk sharing." A tech enterprise's successful R&D of new semiconductor materials with low-interest "R&D expense loans," leading to a 30% export price increase, exemplifies this incentive effect.

In information efficiency, Wang Handi et al. (2022) integrated customs export data (2015–2020), BVD Orbis financial data, and Google Trends search indices to analyze digital finance's impact on information acquisition. They found it improved export product qualification rates by 5%–8% via "reducing market information costs → optimizing product design → enhancing export quality," with post-design optimization order volumes increasing by 40% based on digital transformation surveys. This highlights digital inclusive finance's role in lowering information costs, enhancing market demand capture, and improving information efficiency. Qian Haizhang et al. (2021) found that digital finance significantly boosted disruptive innovation in GEM-listed biopharmaceutical firms, increasing breakthrough patent applications by 20%. Xu Yulian et al. (2023) showed that digital inclusive finance combined with government innovation subsidies increased SME R&D intensity by 0.8 percentage points, demonstrating a "1+1>2" synergy.

2.2. Research on Technological Complexity of Export Products.

The technological complexity of export products is a core dimension of corporate international competitiveness, driven by global market dynamics and micro-level capability building. Academic research has systematically explored macro-environmental, micro-mechanistic, and digital technology-enabling factors.

The intrinsic link between technological complexity and export quality provides a natural extension of research perspectives. Higher technological complexity entails stricter product performance and innovation standards, with quality serving as the ultimate carrier of technology implementation and market validation—whether through technological breakthroughs in emerging industries (e.g., lithium battery energy density improvements, Yu Miaojie, 2022) or process upgrades in traditional manufacturing, both require quality control (e.g., testing equipment investment, quality

process optimization) to translate into competitiveness (Xie Xuanli, 2018; Pan Tong et al., 2024). Shifting from technological complexity to quality research represents an expansion from the "innovation supply side" to the "market demand side." Existing literature has discussed drivers of technological complexity (e.g., digital finance's capital and information enablement, Wang Yuewu & Zhang Yu, 2023; Wang Handi et al., 2022), but specific pathways for transforming technological advantages into quality advantages (e.g., resource prioritization for quality upgrades, data-driven quality design optimization) require further refinement. The following sections review digital inclusive finance's impact on export quality from perspectives of resource allocation efficiency, information matching capability, and industry-specific effects to theoretically underpin the "technology-quality" synergy.

In global market demand structure changes, Liu Zhongli (2021) analyzed export quality using UN Comtrade data and World Bank consumer confidence indices. Strict safety and environmental standards in developed countries (e.g., the EU RoHS Directive covering 60% of Mechanical and Electrical Products exports) have forced Chinese firms to raise quality control standards by over 30%. Emerging markets' (e.g., Southeast Asia, the Middle East) cost-performance demands have inspired "stratified quality strategies," such as Haier's development of high-temperature/low-voltage-adaptive appliances for India, boosting export qualification rates by 12% compared to traditional markets.

Wang Lan (2020) used OECD quality standard data to confirm that international certifications (e.g., ISO 9001, HACCP) significantly enhance export quality: certified firms achieve 40% higher EU market access efficiency and a 25% lower risk of technical trade barriers. Li Kunwang (2019) studied anti-dumping impacts using 2000–2016 industrial enterprise data, finding firms respond to anti-dumping lawsuits by "upgrading quality to avoid tariffs"—for example, photovoltaic enterprises increased polysilicon conversion efficiency from 18% to 22% and export prices by 20% post-EU anti-dumping investigations. General Administration of Customs (2023) data shows RCEP's mutual recognition of technical measures reduced regional certification costs by 35% and improved quality consistency by 28%.

In technological innovation and quality breakthroughs, Yu Miaojie (2022) matched patent and customs data to find that a 10% increase in authorized invention patents raises export technological complexity indices by 1.5 percentage points. Case studies include CATL's 300Wh/kg battery energy density (65% high-end exports via 5,000+ patents) and DJI's 70% global consumer drone market share with 20% higher quality reliability than international competitors. Wu Fuxiang (2023) highlighted the "dual circulation" context, where a 1% increase in domestic sales raises export quality by 0.8% via R&D cost sharing (e.g., Midea validating smart home technologies domestically before exporting). Lin Yifu et al. (2021) found digital finance-supported new energy vehicle firms improved battery energy density by 5% annually, 2 percentage points higher than traditional financing. Mao Qilin (2023) showed digital finance shortened semiconductor core technology breakthrough cycles by 18 months and increased high-end export shares by 25%.

In financial support and quality infrastructure, Xie Xuanli (2018) matched digital inclusive finance indices with customs data to find digital credit tools (e.g., Wangshang Bank's "310" model) increased SME quality testing equipment investment by 20% and laboratory certification rates by 18%. Agricultural enterprises using "digital supply chain finance" achieved 75% export quality traceability system coverage, 40 percentage points higher than traditional financing. Huang Yiping (2020) noted that digital inclusive finance reduces quality upgrade risks via "risk sharing mechanisms": blockchain-based fund tracking keeps non-performing loan rates for quality projects below 3%, 2 percentage points lower than traditional credit.

In data-driven quality adaptation, Wang Zhibo (2022) linked Google Trends and export quality data to show digital information capabilities improved product design-market demand matching by 35%. For example, cross-border e-commerce firms increased clothing fit rates from 60% to 85% and reduced return rates by 15% via consumer review analysis. Alibaba International Station data shows firms using "Data Advisor" tools have 40% lower quality complaint rates than industry averages.

2.3. Literature Review.

While existing studies have revealed export quality drivers from macro-policy, micro-capability, and financial technology perspectives, three gaps remain: 1. Industry heterogeneity deficiency: Most research focuses on traditional industries (textiles, agriculture), lacking in-depth analysis of quality competitiveness in emerging industries (new energy vehicles, biomedicine). 2. Dynamic evolution mechanism absence: No systematic framework exists for export quality's transition from "standard-following" to "standard-leading" (e.g., Huawei's 5G standard internationalization). 3. Green quality standard research lag: With rising green trade barriers (carbon tariffs, ESG ratings), empirical research is needed on how digital inclusive finance aids enterprises in building green quality systems (carbon footprint tracking, eco-tech R&D). Future research could integrate the "dual circulation" strategy to explore synergistic innovation between digital technologies and quality standards, providing targeted theoretical support for enterprises navigating global value chain restructuring.

3. Theoretical Analysis and Research Hypotheses

Digital inclusive finance significantly enhances the technological complexity of enterprises' export products by optimizing resource allocation efficiency. First, digital inclusive finance platforms use big data analysis technologies to accurately assess enterprises' credit profiles and financial risks, effectively alleviating the financing difficulties faced by SMEs in traditional financial systems. Big data risk control systems integrate multi-dimensional information such as enterprise operation data, industry trends, and macroeconomic indicators to construct more comprehensive and accurate enterprise credit portraits. This enables financial institutions like banks to more confidently provide financing support to SMEs that were previously unable to obtain loans due to difficult credit assessments. The expansion of financing channels provides sufficient financial guarantees for enterprises in technological R&D, equipment upgrades, and high-end talent recruitment, allowing them to break through capital bottlenecks and boldly invest resources in improving technological complexity. Second, the information transparency of digital inclusive finance platforms strongly supports the optimization of internal resource allocation in enterprises. The informatization upgrade of enterprise fund management systems enables managers to monitor fund flows in real time and accurately grasp fund usage efficiency, ensuring that funds are preferentially directed to key links in technological complexity improvement, such as R&D investment, new technology introduction, and innovation capability building. This precise fund allocation strategy avoids resource waste and misallocation, greatly enhancing enterprise resource allocation efficiency. For example, enterprises can gradually shift funds from low-efficiency production links to high-tech R&D projects based on detailed analysis reports provided by the platform, laying a solid financial foundation for improving the technological complexity of export products. From the perspective of resource allocation theory, digital inclusive finance achieves optimal internal capital allocation by accurately assessing enterprise credit, expanding financing channels, and enhancing fund usage transparency, thereby providing sufficient momentum and support for upgrading the technological complexity of export products.

Digital inclusive finance effectively promotes enterprises to enhance the technological complexity of export products by strengthening innovation incentive mechanisms. First, after solving financing difficulties, enterprises can more confidently and continuously invest in R&D activities. Sufficient guarantee of R&D funds enables enterprises to purchase advanced R&D equipment, attract high-end technical talents, and carry out long-term innovation projects, which provide necessary conditions for technological breakthroughs and innovation achievements. For example, enterprises can use new funds to establish international cooperative R&D laboratories, collaborate with global top research institutions to jointly tackle technical problems, thereby significantly improving the technological complexity of export products. Second, digital inclusive finance platforms themselves serve as open technical exchange centers, providing convenient platforms for innovation cooperation among enterprises. The platforms gather technical information, market demand data, and industry frontier dynamics of many enterprises. Through these platforms, enterprises can establish cooperative

relationships with others, share technical resources, and accelerate technological iteration and innovation processes. For instance, the platforms can organize online and offline technical exchange activities to promote technical docking and collaborative innovation between upstream and downstream enterprises, enabling enterprises to more quickly absorb external experience and enhance their technical levels and innovation capabilities during technological innovation. Third, risk management services such as insurance provided by digital inclusive finance strongly guarantee enterprises' willingness to take innovative risks. Innovation activities are often accompanied by high risks, such as technical failure risks and market uncertainty risks. Insurance mechanisms can share these risks to a certain extent, giving enterprises greater courage and confidence to invest in the R&D of high-tech complex products. According to Schumpeter's innovation theory, innovation is the core driving force for economic development. Digital inclusive finance stimulates enterprises' innovative vitality by providing financial support, building technical exchange platforms, and sharing innovation risks, enabling enterprises to continuously engage in technological innovation. This ultimately reflects in the significant improvement of the technological complexity of export products, helping enterprises gain a more favorable competitive position in the global market.

Digital inclusive finance comprehensively helps enterprises enhance the technological complexity of export products by improving information efficiency. First, digital inclusive finance platforms integrate massive market information, providing enterprises with rich information resources. This information covers key insights such as global market demand dynamics, industry technology trends, and competitors' product characteristics, enabling enterprises to promptly understand market changes and accurately grasp technological R&D directions. For example, platforms can customize market information reports for different enterprises through big data analysis, detailing the potential demand for specific technical products in target markets, thereby guiding enterprises to optimize R&D strategies and develop high-tech complex products that better meet market needs. Second, digital inclusive finance platforms leverage big data analysis to achieve precise matching between supply and demand, significantly improving market transaction efficiency. By analyzing enterprises' production capabilities, technical levels, and customers' personalized needs, platforms can accurately position potential customer groups for enterprises and recommend optimal market entry points. This precise matching not only reduces market development costs but also enables enterprises to carry out customized R&D and production based on customer needs, thereby enhancing product technological complexity and market competitiveness. For instance, when a platform identifies high demand for products with specific intelligent functions in an emerging market, it can promptly notify relevant enterprises, provide customized product R&D suggestions and technical support, and help enterprises quickly respond to market demands by developing high-tech complex export products. Furthermore, services such as exchange rate risk management provided by digital inclusive finance platforms effectively reduce risks in enterprises' export processes, creating a stable external environment for enhancing the technological complexity of export products. Exchange rate fluctuations often significantly impact enterprises' export profits, while risk management tools provided by platforms—such as foreign exchange forward contracts and foreign exchange options—help enterprises lock in exchange rate risks and stabilize export revenue expectations. This allows enterprises to allocate more resources to technological R&D and product upgrades without excessive worry about uncertainties caused by exchange rate fluctuations. From the perspective of information economics, digital inclusive finance enhances enterprises' information acquisition capabilities and risk response capacities in global markets by reducing information asymmetry, optimizing information utilization efficiency, and providing risk management services. This enables enterprises to focus on technological R&D and product innovation, continuously improve the technological complexity of export products, and thus build long-term competitive advantages in international markets. Based on the above discussions, this paper formulates the following hypothesis.

H1 is as follows:

H1: Digital inclusive finance can significantly improve the technological complexity of export products of listed companies in China.

4. Research Design

4.1. Data Sources.

This study uses Chinese A-share listed companies from 2012 to 2016 as the sample. Data for the explanatory variable (digital inclusive finance) are sourced from the Digital Inclusive Finance Index compiled and measured by Peking University. Data for the dependent variable (technological complexity of export products) are obtained from the import-export database of China Customs. Control variables and mediating variables are collected from the China Stock Market & Accounting Research Database (CSMAR) and Wind Database. Following prior literature, the sample is processed using the following criteria: (1) excluding observations with missing values in key variables; (2) excluding financial and insurance enterprises; (3) excluding ST, *ST, and PT enterprises; (4) winsorizing all variables at the 1% and 99% quantiles. After these treatments, the final sample comprises 8,183 firm-year observations.

4.2. Variable Definitions

4.2.1. Dependent Variable: Export Technological Complexity (esi).

This study measures the technological complexity of enterprises' export products using general trade export volumes. First, the Revealed Comparative Advantage (RCA) coefficient for country c in product k (where k is a product with a HS6 customs code) is calculated. Let x_{ik}/X_i denote the export volume of product k by country c, and X_c denote the total exports of country c:

$$RCA_{ck} = \frac{(x_{ck}/X_c)}{\sum_c x_{ck}/X_c} \quad (1)$$

Second, the technological complexity of product k is obtained by multiplying the RCA of each country in product k by the country's per capita GDP ($rGDP_c$):

$$PRODY_k = \sum_c RCA_{ck} * rGDP_c \quad (2)$$

Finally, the export technological complexity at the product level is converted to the enterprise level. Let x_{ik}/X_i represent the proportion of enterprise i's export volume of product k to its total export volume, and esi_{ci} denotes the final calculated export technological complexity at the enterprise level.

4.2.2. Explanatory Variable: Digital Inclusive Finance (FT)

This study uses the logarithmized "Peking University Digital Inclusive Finance Index" to measure the development level of digital inclusive finance in each prefecture-level city, which is matched with listed companies according to their headquarters' locations. The index covers dimensions such as payment, credit, insurance, and investment, and is constructed by standardizing indicators including mobile payment coverage, online credit availability, and digital wealth management penetration. It comprehensively reflects the breadth and depth of regional digital financial services.

4.2.3. Control Variables

Following the practices of previous scholars, this study controls for the following variables: firm size (Size), debt-to-asset ratio (Lev), return on assets (ROA), return on equity (ROE), total asset turnover (ATO), cash flow ratio (Cashflow), listing age (ListAge), firm age (FirmAge), audit fees (Mfee), and Big Four audit (Big4). Table 1 below provides the specific variable definitions.

Table 1. Variable Definitions

Variable Name	Symbol	Definition
Export Technological Complexity	*esi*	Measurement method is described above.
Digital Inclusive Finance	*FT*	Measurement method is described above.
Firm Size	*Size*	Ln(Total Assets)
Firm Size	*Size*	Ln(Total Assets)
Debt-to-Asset Ratio (Lev)	*Lev*	Total Liabilities / Total Assets
Return on Assets (ROA)	*ROA*	Net Profit / Total Assets
Return on Equity (ROE)	*ROE*	Net Profit / Average Shareholders' Equity
Total Asset Turnover (ATO)	*ATO*	Operating Income / Total Assets
Cash flow ratio	*Cashflow*	(Net Cash Flow from Operating Activities / Total Assets) * 100%
Listing Age (ListAge)	*ListAge*	Ln(Research Year - IPO Year + 1)
Firm age (Firmage)	*FirmAge*	Ln(Research Year - Establishment Year + 1)
Audit Fees (Mfee)	*Mfee*	Audit fees paid by the enterprise
Big Four Audit (Big4)	*Big4*	1 if audited by the Big Four accounting firms in the current year, 0 otherwise

4.3. Model Assumptions

This paper tests the hypothesis using Model (3):

$$esi_{i,t} = \alpha + \beta FT_{i,t} + \gamma Control_{i,t} + IndustryF.E. + TimeF.E. + \varepsilon_{i,t} \quad (3)$$

Among them, $esi_{i,t}$ represents export technological complexity, $FT_{i,t}$ enotes the measurement of digital inclusive finance, $Control_{i,t}$ is a set of control variables, *IndustryF.E* indicates that the model controls for industry effects, *TimeF.E* indicates that the model controls for time effects, and $\varepsilon_{i,t}$ is the error term. The study focuses on the coefficient β. If the coefficient on the right-hand side of the equation is significantly positive, it suggests that digital inclusive finance can promote the technological complexity of enterprises' export products, and hypothesis H1 is validated. Additionally, to address potential cross-sectional heteroscedasticity, all regressions in this paper use robust standard errors clustered at the enterprise level.

5. Empirical Results

5.1. Descriptive Statistics

This paper involves the explanatory variable FT, the dependent variable esi, and ten control variables. Table 2 below presents the descriptive statistics of the main variables. Among them, the dependent variable esi (export technological complexity of enterprises) has a mean value of 663.7 and a standard deviation of 1,075. The explanatory variable FT shows a small difference, indicating that the overall level of digital financial development among enterprises is relatively high.

Table 2. Descriptive Statistical Results

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
esi	8, 183	663.7	1,075	0	5,347
FT	8, 183	5.146	0.242	4.568	5.499
Size	8, 183	22.20	1.281	19.94	25.86
Lev	8, 183	0.428	0.212	0.0530	0.875
ROA	8, 183	0.0420	0.0497	-0.125	0.197
ROE	8, 183	0.0694	0.0941	-0.351	0.310
ATO	8, 183	0.653	0.451	0.0812	2.490
Cashflow	8, 183	0.0455	0.0661	-0.147	0.227
ListAge	8, 183	2.176	0.743	0.693	3.178
FirmAge	8, 183	2.792	0.332	1.792	3.367
Mfee	8, 183	0.102	0.0769	0.0112	0.458
Big4	8, 183	0.0645	0.246	0	1

5.2. Benchmark Regression Analysis

This study conducts regression analysis based on Model (3) specified in the model assumptions with results presented in Table 3. Column (1) reports the benchmark regression model containing only the core explanatory variable and the dependent variable without introducing fixed effects or control variables. Column (2) incorporates industry and year fixed effects into the benchmark model. Column (3) adds control variables such as firm size (Size) to the benchmark model. Column (4) includes both fixed effects and control variables to comprehensively account for potential omitted variables and heterogeneity effects. From Columns (1) to (4) in Table 3 the coefficients of digital inclusive finance (FT) are all positive and significant at the 1% level strongly supporting the core hypothesis of this paper. This indicates that digital inclusive finance has a significant positive effect on the export technological complexity (esi) of enterprises. A deeper analysis of the control variables reveals that firm size (Size) debt-to-asset ratio (Lev) return on assets (ROA) return on equity (ROE) total asset turnover (ATO) cash flow ratio (Cashflow) listing age (ListAge) firm age (FirmAge) audit fees (Mfee) and Big Four audit (Big4) all influence enterprise export technological complexity to varying degrees. Specifically: - The negative coefficient of firm size (Size) may stem from the fact that larger enterprises have diversified operations and may not focus on exporting high-tech complexity products. - The negative coefficient of debt-to-asset ratio (Lev) suggests that high debt levels may constrain enterprises from investing in R&D to improve export technological complexity. - The positive coefficient of Big Four audit (Big4) confirms that enterprises audited by the Big Four accounting firms are more likely to gain the trust of overseas partners due to the superior quality of their audits thereby positively impacting export technological complexity.

Table 3. Benchmark Regression Results

	(1)	(2)	(3)	(4)
VARIABLES	*esi*	*esi*	*esi*	*esi*
FT	196.753***	729.389***	325.369***	536.589***
	(4.101)	(4.692)	(6.351)	(3.457)
Size			-23.423	-7.996
			(-1.281)	(-0.451)
Lev			-360.518***	-134.460
			(-3.155)	(-1.254)
ROA			-1,351.967	-1,368.035
			(-1.503)	(-1.643)
ROE			173.362	750.402**
			(0.489)	(2.253)
ATO			-1.562	-87.456**
			(-0.040)	(-1.996)
Cashflow			338.814	227.078
			(1.497)	(1.091)
ListAge			-283.550***	-224.531***
			(-8.364)	(-6.887)
FirmAge			-179.054**	-137.553**
			(-2.481)	(-2.040)
Big4			82.472	59.061
			(0.991)	(0.742)
Mfee			-804.005***	-384.499
			(-3.380)	(-1.642)
Constant	-348.744	-2,419.567***	887.642**	-396.397
	(-1.391)	(-2.941)	(2.049)	(-0.418)
Observations	8,183	8,183	8,183	8,183
R-squared	0.002	0.195	0.069	0.226
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Note:***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, with t-values in parentheses (the same below).

6. Further Analysis

6.1. Robustness Test

6.1.1. Replacement of Fixed Effects

To verify the robustness of the impact of digital inclusive finance (FT) on enterprises' export technological complexity (esi), this paper further changes the fixed effects from the industry level to the enterprise level and re-conducts the regression analysis. The results are shown in Table 4. In Column (1), the coefficient of FT is positive (140.250) and significant at the 1% level. After introducing control variables (Column 2), the coefficient of FT remains positive (762.084) and larger than before. In Column (3), the coefficient of FT is positive (352.678) and significant at the 1% level. When both enterprise-level fixed effects and control variables are introduced (Column 4), the coefficient of FT is positive (96.309) and significant at the 1% level. These results indicate that the positive impact of digital inclusive finance on enterprises' export technological complexity is robust.

Table 4. Measurement Results of Replacing Fixed Effects

	(1)	(2)	(3)	(4)
VARIABLES	*esi*	*esi*	*esi*	*esi*
FT	140.250***	762.084***	352.678***	96.309***
	(4.194)	(3.311)	(8.760)	(3.397)
Size			0.513	-13.491
			(0.032)	(-0.418)
Lev			-287.095***	3.751
			(-3.180)	(0.033)
ROA			-1,306.425**	-627.438
			(-2.246)	(-1.099)
ROE			235.292	167.204
			(1.065)	(0.732)
ATO			-42.256	-105.391*
			(-1.266)	(-1.931)
Cashflow			207.933	-161.514
			(1.233)	(-0.978)
ListAge			-275.286***	-107.265
			(-9.094)	(-1.463)
FirmAge			-154.507**	-253.957
			(-2.229)	(-0.820)
Big4			25.239	-82.355
			(0.355)	(-0.645)
Mfee			-449.319**	48.258
			(-2.335)	(0.206)
Constant	-35.378	4,422.059***	87.025	5,856.716***
	(-0.201)	(4.019)	(0.233)	(3.433)
Observations	8,183	8,183	8,183	8,183
R-squared	0.004	0.233	0.009	0.235
Number of stkcd	2,018	2,018	2,018	2,018
Company FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

6.1.2. Propensity Score Matching (PSM)

To mitigate the impact of sample selection bias on the relationship between digital inclusive finance (FT) and enterprises' export technological complexity (esi), this paper employs the propensity score matching method to address self-selection bias. The results are presented in Table 5. After correcting for self-selection bias, the coefficient of FT remains significantly positively correlated with esi at the 10% level, demonstrating the robustness of the model. **Table 5 Results of Propensity Score Matching.

Table 5. Results of Propensity Score Matching

	(1)	(2)	(3)	(4)
VARIABLES	*esi*	*esi*	*esi*	*esi*
FT	98.576*	636.083***	144.381**	406.944**
	(1.800)	(3.969)	(2.471)	(2.540)
Size			-23.197	-0.842
			(-1.259)	(-0.046)
Lev			-371.515***	-171.862
			(-3.098)	(-1.490)
ROA			-1,371.681	-1,510.013*
			(-1.416)	(-1.671)
ROE			175.606	797.501**
			(0.467)	(2.201)
ATO			6.491	-84.529*
			(0.156)	(-1.847)
Cashflow			364.093	303.683
			(1.468)	(1.313)
ListAge			-294.012***	-232.614***
			(-7.964)	(-6.548)
FirmAge			-176.138**	-116.011
			(-2.260)	(-1.596)
Big4			74.643	39.262
			(0.792)	(0.439)
Mfee			-825.410***	-388.521
			(-3.155)	(-1.524)
Constant	300.106	-1,843.595**	1,803.139***	160.896
	(1.021)	(-2.138)	(3.840)	(0.163)
Observations	6,323	6,323	6,323	6,323
R-squared	0.000	0.198	0.072	0.230
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

6.1.3. Instrumental Variable (IV) Method

Although this paper has attempted to control relevant variables as much as possible, potential endogeneity issues still exist: On one hand, the development of digital inclusive finance (FT) may promote the concentration of capital in local markets, making it difficult to facilitate foreign direct trade of small and medium-sized enterprises; On the other hand, there are many factors affecting enterprises' export technological complexity (esi), and the control variables involved in the current data are insufficient to prevent the occurrence of omitted variables. To address the potential endogeneity in the relationship between FT and esi, this paper uses an **industry-average-based instrumental variable (IV)** to test the model's robustness and further controls for endogeneity through **two-stage least squares (2SLS)**. The first step of the two-stage least squares method is to introduce the instrumental variable into the regression model to verify its correlation with the endogenous variable. As shown in column (1) of Table 6, the instrumental variable is highly correlated with the endogenous variable and significantly positively correlated, with a coefficient of 0.944 and significance at the 1% level, indicating that the selected instrumental variable is highly valid. In the second step, based on the regression results of the first step, predicted fitted values of the endogenous variable are generated and substituted for the original endogenous variable in the benchmark regression. This approach can effectively eliminate the endogeneity caused by endogenous explanatory variables. The results show that after controlling for endogeneity, the coefficient of the core explanatory variable FT is 1,870.669, which is significant at the 5% level. This result further validates the robustness of the core conclusion of this paper: that digital inclusive

finance has a significant promoting effect on enterprises' export technological complexity even when endogeneity is considered.

Table 6. Results of Industry-Average-Based Instrumental Variables

	(1)	(2)
VARIABLES	*FT*	*esi*
iv	0.944***	
	(8.395)	
FT		1,870.669**
		(2.122)
Size	-0.002	-5.444
	(-0.643)	(-0.294)
Lev	-0.027	-232.007*
	(-1.462)	(-1.938)
ROA	0.159	-1,131.626
	(1.317)	(-1.216)
ROE	0.020	837.211**
	(0.376)	(2.307)
ATO	0.018**	-42.242
	(2.538)	(-0.817)
Cashflow	0.000	299.421
	(0.012)	(1.292)
ListAge	-0.016***	-269.394***
	(-3.445)	(-6.720)
FirmAge	-0.010	-139.104*
	(-0.997)	(-1.870)
Big4	0.053***	160.725
	(4.872)	(1.469)
Mfee	0.088**	-184.233
	(2.083)	(-0.665)
Constant	0.350	11,164.473*
	(0.653)	(1.815)
Observations	8,183	8,183
Industry FE	YES	YES
Year FE	YES	YES

6.2. Heterogeneity Analysis

6.2.1. Regional Heterogeneity

Although China's digital finance development has shown an overall upward trend, significant disparities exist across regions, with the largest gap between eastern and western regions continuing to widen. Eastern coastal areas took the lead in piloting policies such as free trade zones and cross-border financial reforms, lowering the threshold for enterprises' foreign trade. In contrast, policies in central and western regions primarily focus on boosting local economic development. The eastern region has a higher per capita GDP and greater corporate digitalization, but these advantages have not significantly translated into improvements in enterprises' export technological complexity (esi). By comparison, enterprises in the western region demonstrate stronger potential to enhance esi driven by digital inclusive finance (FT). The eastern region has a solid industrial foundation, with the Yangtze River Delta and Pearl River Delta forming globally embedded industrial clusters in electronic information, high-end equipment, and other sectors. However, the advantages of these clusters are not significantly reflected in the improvement of esi. Most enterprises in central and western regions are engaged in resource-based or low-end manufacturing, but western enterprises supported by FT can better leverage policy dividends and technological innovation to achieve

significant esi upgrades. Additionally, regulatory authorities in the western region, under the policy support of FT, prioritize the promotion of innovative businesses, reducing the compliance costs for enterprises to improve esi and further driving its growth. Therefore, this paper divides listed companies into three groups by province: eastern, central, and western regions, with results shown in Table 7. The coefficients for eastern and central regions are insignificant, while the coefficient for the western region is significantly positive at the 1% level. This indicates that FT has the most pronounced positive effect on esi in western enterprises, while its effects in eastern and central regions are insignificant. These findings confirm the strong spatial heterogeneity of FT, highlighting significant differences in its impact on esi across regions.

Table 7. Results of Regional Heterogeneity

	(1)	(2)	(3)
Variables/Groups	Eastern Region	Central Region	Western Region
FT	22.193	618.822	809.229***
	(0.096)	(1.421)	(2.728)
Size	13.172	-46.800	0.532
	(0.582)	(-1.128)	(0.013)
Lev	-166.422	148.290	-502.989*
	(-1.153)	(0.573)	(-1.786)
ROA	-1,891.365	-1,281.988	-684.237
	(-1.644)	(-0.688)	(-0.295)
ROE	1,157.156**	770.574	-415.189
	(2.358)	(1.001)	(-0.525)
ATO	-95.621	-159.582*	100.180
	(-1.636)	(-1.829)	(0.801)
Cashflow	322.605	108.083	155.474
	(1.136)	(0.195)	(0.266)
ListAge	-240.565***	-242.785***	-112.774
	(-5.769)	(-2.726)	(-1.083)
FirmAge	-24.906	-451.047**	-261.149
	(-0.306)	(-2.358)	(-1.282)
Big4	-47.713	257.560	450.955
	(-0.492)	(1.199)	(0.903)
Mfee	-133.317	-998.496	-311.689
	(-0.420)	(-1.586)	(-0.478)
Constant	1,145.161	1,828.304	-2,570.884
	(0.825)	(0.786)	(-1.102)
Observations	4,192	1,238	893
R-squared	0.248	0.263	0.198
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

6.2.2. Ownership Heterogeneity

This paper examines the impact of digital inclusive finance (FT) by dividing enterprises into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) based on ownership. SOEs generally face "soft budget constraints," relying on implicit government guarantees to obtain low-cost credit, which weakens their incentive to optimize financing structures through FT. In contrast, private enterprises face hard budget constraints and need FT to reduce financing costs and improve cross-border capital allocation efficiency. SOEs must balance economic and social objectives, thus tending to engage in foreign trade with less developed countries and regions (e.g., African nations), while non-SOEs focus more on developed economies or emerging markets. In innovation, SOEs often have more complex processes, leading to longer timeframes for new technology development and implementation, whereas private enterprises can streamline approval procedures and accelerate

innovation deployment. In regulation, SOEs face stricter state oversight, including tight control over foreign exchange quotas, while non-SOEs encounter fewer constraints in foreign trade and hold a comparative advantage. Long-term credit discrimination in traditional financial systems has left non-SOEs with significantly higher financing constraints than SOEs, which FT can effectively alleviate.

The empirical results in Table 8 show that the FT coefficient for non-SOEs is larger and significant at the 5% level, indicating that their export technological complexity (esi) is more sensitive to FT. This confirms that FT has a more pronounced positive effect on esi in non-SOEs, consistent with the theoretical arguments above.

Table 8. Results of Enterprise Ownership

	(1)	(2)
Variables/Groups	State-Owned Enterprises (SOEs)	Non-State-Owned Enterprises
FT	363.070	492.427**
	(1.516)	(2.281)
Size	-11.144	23.987
	(-0.453)	(0.843)
Lev	-76.669	-275.179*
	(-0.452)	(-1.706)
ROA	766.713	-2,432.239**
	(0.474)	(-2.073)
ROE	85.919	1,046.213*
	(0.153)	(1.911)
ATO	-108.465	-41.427
	(-1.579)	(-0.629)
Cashflow	219.405	295.812
	(0.620)	(0.964)
ListAge	-234.697***	-257.213***
	(-3.307)	(-5.956)
FirmAge	-67.673	-117.695
	(-0.511)	(-1.385)
Big4	24.280	63.529
	(0.220)	(0.420)
Mfee	-858.646**	-94.718
	(-2.026)	(-0.288)
Constant	163.171	-551.804
	(0.118)	(-0.428)
Observations	2,773	3,550
R-squared	0.180	0.257
Industry FE	YES	YES
Year FE	YES	YES

6.2.3. CEO-Chairman Duality

Enterprises with CEO-chairman duality (i.e., the same individual serving as both CEO and board chairman) may exhibit higher decision-making efficiency, enabling them to more rapidly respond to opportunities brought by digital inclusive finance (FT) and thus utilize FT more effectively to enhance export technological complexity. For example, a single decision-maker can more easily coordinate internal resources to drive technological innovation and market expansion. Additionally, the management of such enterprises may be more inclined to adopt proactive strategies to enhance the firm's technological competitiveness and strengthen its position in international markets. In contrast, non-duality enterprises, whose decision-making processes involve coordination among multiple stakeholders, may lag in leveraging FT to improve export technological complexity. Nevertheless, non-duality enterprises may have more balanced governance structures, helping to avoid overly risky decisions and ensuring steady corporate development to some extent.

This paper further explores the differences in the impact of digital inclusive finance (FT) on enterprises' export technological complexity (esi) between firms with CEO-chairman duality (where the chairman and general manager are the same person) and those without such duality (where the chairman and general manager are different individuals). According to the regression results in Table 9, the FT coefficient for enterprises with CEO-chairman duality is 875.972, significantly positive at the 1% level, indicating that digital inclusive finance has a notable promoting effect on the export technological complexity of such enterprises. In contrast, the FT coefficient for non-duality enterprises is 235.732, which is positive but only significant at the 10% level and not statistically strong, suggesting a relatively weak promoting effect.

Table 9. CEO-Chairman Duality

	(1)	(2)
Variables/Groups	Enterprises with CEO-Chairman Duality	Enterprises without CEO-Chairman Duality
FT	875.972***	235.732
	(2.607)	(1.331)
Size	30.869	-5.124
	(0.770)	(-0.254)
Lev	-131.961	-176.820
	(-0.545)	(-1.366)
ROA	221.950	-1,945.885*
	(0.119)	(-1.921)
ROE	142.970	895.042**
	(0.181)	(2.225)
ATO	-86.461	-85.551*
	(-0.764)	(-1.696)
Cashflow	-236.008	535.721**
	(-0.480)	(2.059)
ListAge	-165.946**	-253.210***
	(-2.406)	(-6.241)
FirmAge	-161.777	-99.231
	(-1.230)	(-1.235)
Big4	-201.074	81.640
	(-1.306)	(0.840)
Mfee	-145.084	-543.384*
	(-0.248)	(-1.887)
Constant	-3,358.484*	1,210.506
	(-1.703)	(1.104)
Observations	1,434	4,840
R-squared	0.261	0.222
Industry FE	YES	YES
Year FE	YES	YES

6.3. Mechanism Analysis

Digital inclusive finance (FT) comprehensively aids enterprises in enhancing the technological complexity of export products by optimizing resource allocation efficiency, strengthening innovation incentive mechanisms, and improving information efficiency. It uses big data to accurately assess enterprise credit, broaden financing channels, optimize capital allocation, and support technological R&D and equipment upgrading. Meanwhile, it promotes technological exchange and cooperation among enterprises through platforms, shares innovation risks, and stimulates corporate innovation vitality. Additionally, it integrates market information, precisely matches supply and demand, provides risk management services, reduces market risks for enterprises, and helps develop high-tech

complex products that better meet market demands. Based on this, this paper employs a two-step mechanism analysis method, with the formula shown in Equation (4):

$$M_{i,t} = \alpha + \beta FT_{i,t} + \gamma Control_{i,t} + IndustryF.E. + TimeF.E. + \varepsilon_{i,t} \quad (4)$$

Among them, $M_{i,t}$ represents the mediating variable, $FT_{i,t}$ represents digital inclusive finance, and $Control_{i,t}$ represents control variables. The mediating variables are measured by different methods: resource allocation efficiency (Overinvest) is measured by the degree of corporate overinvestment. First, the appropriate investment level of the enterprise in the current year is estimated through the data of the previous year, and then the difference is obtained by subtracting the estimated value from the actual investment level of the enterprise in the current year. If the difference is greater than 0, the difference measures the degree of corporate overinvestment; if the difference is less than 0, it means the enterprise is underinvested, and at this time, Overinvest is set to 0. Innovation incentives are measured by the proportion of enterprise R&D investment in operating expenses (RD) and the number of patents (Patent); information efficiency is measured by stock price synchronicity (SYN). The results are shown in Table 10. For the proportion of enterprise R&D investment (RD) and the number of patents (Patent), the coefficients of FT are significantly positive at the 1% level, indicating that digital inclusive finance can significantly promote enterprise innovation incentives, thereby promoting the improvement of enterprise export technological complexity; for enterprise resource allocation efficiency, the coefficient of FT is significantly negative under the 5% condition, indicating that digital inclusive finance promotes the improvement of enterprise export technological complexity by inhibiting enterprise overinvestment; for information efficiency, the coefficient of FT is significantly negative at the 5% level, indicating that digital inclusive finance inhibits enterprise stock price synchronicity, improves information efficiency, and further facilitates foreign trade and the improvement of export technological complexity.

Table 10. Results of Mechanism Analysis

	(1)	(2)	(3)	(4)
VARIABLES	*RD*	*Patent*	*Overinvest*	*SYN*
FT	0.011***	0.607***	-0.129**	-0.049**
	(4.272)	(2.611)	(-2.212)	(-2.278)
Size	0.000	0.578***	0.006	0.018***
	(0.403)	(16.899)	(0.629)	(6.203)
Lev	-0.001	-0.008	0.117*	-0.127***
	(-0.534)	(-0.042)	(1.721)	(-7.076)
ROA	0.045***	2.024*	-0.690**	-0.453***
	(2.830)	(1.658)	(-2.101)	(-3.258)
ROE	0.006	0.691	0.362*	-0.007
	(0.981)	(1.202)	(1.768)	(-0.100)
ATO	0.013***	0.404***	-0.038**	-0.018**
	(9.810)	(4.963)	(-2.041)	(-2.231)
Cashflow	0.009**	-0.829**	0.395***	0.012
	(2.159)	(-2.348)	(3.035)	(0.304)
ListAge	-0.001**	-0.067	0.024*	-0.003
	(-2.035)	(-1.427)	(1.952)	(-0.724)
FirmAge	-0.003***	-0.151	0.022	-0.001
	(-2.669)	(-1.480)	(1.520)	(-0.077)
Big4	-0.001	0.097	-0.003	-0.032**
	(-0.502)	(0.615)	(-0.128)	(-2.443)
Mfee	0.101***	2.952***	-0.030	-0.127***
	(8.314)	(6.471)	(-0.224)	(-2.897)
Constant	-0.053***	-14.347***	0.398	0.560***
	(-3.528)	(-10.684)	(0.690)	(4.490)
Observations	6,323	6,323	5,899	6,203
R-squared	0.477	0.448	0.017	0.219
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

7. Conclusions and Policy Recommendations

China's economy is currently in a critical transition from "scale expansion" to "quality improvement," with an urgent need for high-quality development in the foreign trade sector. As a key innovation in financial technology, digital inclusive finance (FT) provides more efficient and equitable financial services to small and medium-sized enterprises (SMEs), significantly enhancing the technological complexity of their export products. This paper empirically verifies the positive impact of FT on enterprises' export technological complexity and reveals its mechanism of action. The results show that FT comprehensively aids enterprises in improving export product technological complexity by optimizing resource allocation, strengthening innovation incentives, and enhancing information efficiency. Additionally, heterogeneity analysis finds that the impact of FT varies significantly across regions, enterprise ownership types, and governance structures, with particularly pronounced effects in western regions, non-state-owned enterprises, and firms with CEO-chairman duality. Mechanism analysis further confirms that optimized resource allocation, enhanced innovation incentives, and improved information efficiency are important pathways through which FT influences export technological complexity.

This study provides a new perspective for understanding the role of FT in promoting enterprise technological innovation and international competitiveness, and offers useful references for policymakers. Future research could further explore the mechanisms of FT across different industries and enterprise scales, as well as how to optimize the development environment of FT through policy guidance to better support the high-quality development of the real economy.

References

[1] Pan Tong, Li Hua, and Guo Lu. The Impact of Digital Finance on the Quality of Export Products of Small and Medium-sized Enterprises —— An Empirical Analysis Based on Cross-border E-commerce Platform Data [J]. International Trade Issues, 2024 (03): 129 - 143.

[2] Li Hua. The Impact of Digital Inclusive Finance on the Export Quality of Agricultural Enterprises: An Empirical Analysis Based on Multi-source Data [J]. Agricultural Economic Issues, 2024 (03): 106 - 118.

[3] Liu Guiping. Development of Digital Inclusive Finance and Innovation of Small and Medium-sized Enterprises [J]. China Finance, 2020 (15): 59 - 61.

[4] Wang Yuewu and Zhang Yu. Digital Inclusive Finance, Supply Chain Concentration, and Enterprise Innovation [J]. Caijing Theory and Practice, 2023, 44 (03): 62 - 68.

[5] Wang Handi, Zhang Yu, and Li Ming. Digital Finance and the Quality of Enterprise Export Products: A Perspective Based on Information Utilization Efficiency [J]. International Trade Issues, 2022 (09):106 - 120.

[6] Liu Zhongli. Changes in Global Market Demand Structure and Upgrading of China's Export Quality [J]. World Economic Research, 2021 (03): 113 - 124+136.

[7] Wang Lan. The Impact of Global Value Chain Embedding on the Quality of China's Manufacturing Exports —— An Analysis Based on Industry Heterogeneity and Quality Added Value [J]. Finance & Trade Economics, 2020, 41 (04):109 - 124.

[8] Li Kunwang, Jiang Wei, and Song Ligang. Anti-dumping Investigation and the Quality Upgrade of China's Export Products [J]. Economic Research, 2019, 54 (03): 127 - 142.

[9] Yu Miaojie and Zhang Rui. How does innovation influence the quality upgrade of Chinese enterprises' export products? [J]. Economic Research, 2022, 57 (06): 136 - 153.

[10] Wu Fuxiang and Wang Liudi. Domestic market, technology spillovers and export quality improvement —— An Empirical Analysis of Chinese Manufacturing Enterprises [J]. International Trade Issues, 2023 (03): 90 - 104.

[11] Xie Xuli, Wang Shihui, Zheng Zhilai, Zhang Haoxing, Shen Yan. Can digital finance promote innovation in small and micro enterprises? —— Evidence Based on the Digital Inclusive Finance Index of Peking University and Patent Data from the National Intellectual Property Administration [J]. Economic Research, 2018, 53 (11): 125 - 139.

[12] Huang Yiping and Huang Zhuo. Main Models and Risks of Digital Finance [J]. China Finance, 2020 (03): 18 - 20.

[13] Wang Zhibo. Data-driven Quality Adaptation and Export Upgrading [J]. World Economy, 2022, 45 (06):136 - 158.

[14] Yin Zhichao, Zhang Haodong, and Li Quan. Digital Inclusive Finance and Innovation of Rural SMEs [J]. Financial Research, 2020 (11): 123 - 138.

[15] Zhang Yilin, Lin Chuan, and Wu Kangping. Digital Finance and Innovation of High-tech Enterprises [J]. Economic Research, 2022 (05): 148 - 163.

[16] Qian Hai Zhang, Wang Yao Hui, and Chen Jin. Digital Inclusive Finance and Disruptive Innovation [J]. Management World, 2021 (08): 135 - 150.

[17] Xu Yulian, Wang Hongqi, and Zhang Sixue. The Synergistic Effect of Digital Finance and Government Subsidies: An Innovative Approach to Incentives [J]. China Soft Science, 2023 (03): 132 - 145.

[18] Lin Yifu, Sun Ang, and Zhang Pengfei. Digital Finance and the Upgrading of the New Energy Vehicle Industry [J]. China Industrial Economics, 2021 (09): 81 - 98.

[19] MAO Qilin. Digital Finance and Enterprise Core Technology Breakthrough [J]. Financial Research, 2023 (04): 113 - 129.