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ARTICLE

Impact of Manufacturing Subsidies on Global Trade Competitiveness under Smart Finance

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ABSTRACT

This study examines how intelligent finance transforms the transmission mechanism of manufacturing and agricultural subsidy policies in shaping national trade competitiveness. The analysis employs a sector-matched panel of 30 countries from 2018 to 2023, integrating UN Comtrade and WTO trade data, OECD subsidy accounts, and a composite intelligent-finance index that combines AI penetration with financial-institution investment. An agricultural coverage scalar, reflecting digital crop insurance and AI-based rural credit, extends the cross-sector comparison. The results from two-way fixed effects and robustness checks using RCA indices reveal that subsidies enhance trade competitiveness, while intelligent finance magnifies this effect through targeted allocation, digital monitoring, and precision in capital flow. The impact operates through three channels: technological innovation, production efficiency, and risk management. Manufacturing gains arise from R&D investment, robotization, and supply-chain resilience; agriculture benefits from digital insurance participation, technology adoption, and logistics reliability. Effects are stronger in economies with advanced digital finance systems and weaker where infrastructure or connectivity remains limited. Policy relevance lies in aligning with the OECD Green Growth Report (2024) and the WTO trade-distortion framework, which emphasize transparent, innovation-driven subsidy governance. Embedding intelligent finance into subsidy systems strengthens efficiency, accountability, and sustainability, advancing global competitiveness in both industrial products and agricultural commodities.

Keywords: Intelligent Finance; Subsidy Policy; Trade Competitiveness; Manufacturing; Agriculture; Digital Crop Insurance; Two-Way Fixed Effects

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1. Introduction

The deep integration of the digital economy and global industrial chains has reshaped financial systems through the emergence of intelligent finance. As a product of artificial intelligence and financial innovation, intelligent finance optimizes capital allocation and risk management, embodying "technology empowerment" and "efficiency enhancement." AI-driven supply chain finance integrates real-time production and logistics data to optimize credit allocation, subsidy timing, and risk monitoring. The Global Intelligent Finance Development Report (2024) defines this transformation as a critical stage in how finance supports the real economy [1].

In the global marketplace, manufacturing and agricultural competition has intensified. Subsidy policies have become key instruments for safeguarding industrial capacity, food security, and export performance. OECD data show that in 2023, manufacturing subsidies in major economies rose by 18% year-on-year, while WTO statistics indicate agricultural support exceeded USD 540 billion [2, 3], mostly concentrated in cereals and oilseeds. Examples such as the U.S. CHIPS and Science Act and the European Union's Common Agricultural Policy (CAP) highlight subsidies' dual role in promoting technological leadership and agricultural stability [4, 5]. Yet the outcomes vary. South Korea's semiconductor trade competitiveness index rose from 0.32 in 2018 to 0.45 in 2023, while the EU's CAP achieved yield stability but caused market disputes due to surplus exports. China's targeted maize and soybean subsidies reduced production costs and narrowed price gaps with imports, enhancing export competitiveness. These contrasting cases expose a persistent mismatch between policy input and competitiveness output across sectors.

Intelligent finance provides a mechanism to bridge this gap by improving how subsidies are transmitted and monitored. Big data analytics allow governments to identify high-potential firms and farming households, enhancing precision in subsidy targeting. In agriculture, AI-powered insurance and credit platforms predict climate risks, optimize compensation, and monitor fund utilization to prevent resource distortion. Intelligent rural finance reduces transaction costs and improves capital access for smallholders, fostering more resilient agricultural value chains.

This research addresses two unresolved issues. One concerns how intelligent finance moderates the link between subsidy policies and trade competitiveness across industrial and agricultural domains. The other examines how national institutions and sectoral structures influence the strength of this relationship. Current global studies seldom integrate these dimensions, limiting their explanatory and policy relevance. To fill this gap, this paper develops a cross-sectoral empirical framework combining manufacturing and agriculture to assess how intelligent finance enhances the efficiency of subsidy policies and promotes global trade competitiveness.

From a theoretical standpoint, this study connects to three foundational perspectives. Under comparative advantage theory, subsidies reshape cost structures and export specialization. Endogenous growth theory implies that intelligent finance accelerates technological accumulation and innovation-driven productivity gains. From the lens of institutional economics, digitalized finance improves information transparency and regulatory efficiency, reducing distortions in subsidy allocation. This theoretical synthesis provides a foundation for explaining how intelligent finance mediates and amplifies the impact of subsidy policies on national trade competitiveness, aligning with international frameworks such as the OECD Green Growth Report (2024) and the WTO's trade-distortion principles.

2. Literature Review

2.1. The Concept and Mechanisms of Intelligent Finance

Intelligent finance represents the integration of artificial intelligence and financial management, enabling data-driven decision-making and precise policy execution [6, 7]. Its core function is to enhance the efficiency of resource allocation, risk control, and financial supervision. In manufacturing, intelligent finance facilitates real-time subsidy disbursement and risk prediction through AI-based credit assessment and supply chain monitoring. By linking production, logistics, and capital flows, it strengthens firms' capacity for technological innovation and operational coordination. In agriculture, digital financial tools such as AI-scored credit and automated insurance systems improve inclusivity and accountability. They reduce transaction costs, expand access to credit, and ensure that subsidies are distributed to productive and compliant recipients. Through these mechanisms, intelligent finance operates as both a financial innovation and a governance instrument that promotes transparency, stability, and efficiency across sectors.

2.2. Research on Manufacturing and Agricultural Subsidy Policies

Manufacturing and agricultural subsidy policies are central to national strategies for enhancing industrial strength and food security. Research on manufacturing subsidies emphasizes their dual role in stimulating R&D and mitigating market inefficiencies. Empirical evidence shows that targeted subsidies promote technological upgrading and export expansion but may also lead to resource misallocation [8–10] if poorly supervised. In agriculture, subsidies have stabilized production and rural income but often create price distortions and international trade frictions. The OECD and WTO have both highlighted that data-sharing and intelligent supervision systems are critical for reducing subsidy inefficiency. This growing consensus underscores the need to incorporate digital technologies into policy design to achieve balanced outcomes between industrial competitiveness and agricultural sustainability.

2.3. Determinants of Trade Competitiveness in Manufacturing and Agriculture

Trade competitiveness arises from a complex interplay of policy, technology, and financial conditions. In manufacturing, competitiveness improves through innovation, cost reduction, and efficient supply chains. High R&D intensity, automation, and reliable logistics networks increase firms' ability to compete globally. In agriculture, competitiveness depends on yield performance, market access, and resilience to climate and price fluctuations. Subsidies can elevate export capacity by supporting mechanization, input use, and risk insurance. Financial development also matters: digital credit systems enhance liquidity and investment in productivity-enhancing technologies. The TC and RCA indices are widely used to evaluate competitiveness dynamics over time [11, 12]. Evidence indicates that while manufacturing responds to capital accumulation and technological diffusion, agriculture remains constrained by biological cycles and environmental uncertainty. These sectoral differences highlight the necessity of analyzing competitiveness within an integrated, cross-sectoral framework.

2.4. Theoretical Integration and Research Hypotheses

Existing studies have explored the individual effects of subsidies and financial innovation, but rarely the interaction between them [13–15]. Most analyses focus on one-dimensional relationships—either the influence of subsidies on competitiveness or the efficiency gains from intelligent finance—without examining how digital finance mediates or amplifies subsidy effects. The relationship among intelligent finance, subsidies, and competitiveness remains conceptually fragmented. Manufacturing and agriculture differ in production intensity, policy dependency, and technological adoption; yet comparative evidence on how intelligent finance moderates these relationships is limited.

This research builds a unified analytical framework linking subsidies, intelligent finance, and trade competitiveness. It assumes that intelligent finance strengthens the effectiveness of subsidies through three mechanisms:

(1) Promoting technological innovation and R&D efficiency,
(2) Improving production and operational performance via digital supervision,
(3) Reducing information asymmetry and fiscal leakage through data transparency.

Differences in national infrastructure and industrial maturity determine the magnitude of these effects. The study, aligned with the OECD Green Growth Report (2024) and WTO trade-distortion frameworks, seeks to validate these mechanisms across sectors. Existing literature has not systematically verified intelligent finance as a moderating variable, nor has it compared its influence between manufacturing and agriculture. Addressing this gap provides both theoretical refinement and empirical guidance for policy coordination in the era of smart finance.

3. Data Samples and Variable Definitions

3.1. Determination of Sample Scope

The empirical analysis is based on panel data from the manufacturing and agricultural sectors of 30 representative countries over the period 2018–2023, yielding 180 observations prior to data screening. Country selection reflects a combination of industrial structure, the level of intelligent finance development, and subsidy intensity, ensuring coverage across different income groups and policy regimes. Developed economies, including the United States, Japan, Germany, and Singapore, are characterized by mature manufacturing systems and advanced adoption of AI-enabled financial technologies supported by robust digital infrastructure. In contrast, developing economies such as China, India, Brazil, and Mexico display more diversified industrial–agricultural structures and deeper integration into global value chains. China represents a large-scale manufacturing economy, while India and Vietnam are more strongly oriented toward labor-intensive exports, particularly in textiles and electronics. This cross-country composition enables comparative analysis of subsidy effectiveness and intelligent finance across heterogeneous economic contexts.

The agricultural dimension captures major producers and exporters, ensuring sectoral comparability. Brazil contributes as the leading soybean exporter, with agricultural GDP exceeding USD 500 billion. Thailand represents a climate-sensitive rice exporter with dynamic subsidy use, while the United States combines leadership in both manufacturing and maize production under extensive crop insurance. The European Union is represented collectively through CAP data, encompassing cereals, dairy, and oilseeds. This cross-sectoral composition enables the assessment of how subsidies and intelligent finance jointly affect competitiveness in both industrial and food systems.

Representativeness is validated by coverage ratios. In 2023, the sample accounted for 82% of global manufacturing value-added and 85% of manufacturing exports (World Bank, UN Comtrade). In agriculture, the same countries contributed more than 75% of global maize, soybean, and rice exports, and 70% of wheat trade flows (WTO, FAO). The 2018–2023 period was chosen for its data consistency and policy relevance. Intelligent finance indicators became systematically available from 2018 onward in BIS and Wind databases, while the interval encompasses significant global shocks—COVID-19, U.S.–China trade frictions, and disruptions to agricultural supply chains following the Ukraine conflict—allowing analysis under both stable and volatile conditions.

3.2. Data Sources and Verification

All data derive from authoritative international databases and were cross-verified for internal consistency. Manufacturing subsidy data come from the OECD Manufacturing Subsidy Reports (2019–2024) [16], disaggregated into R&D, production, and export components. Missing records for specific economies were filled using official industrial policy bulletins, maintaining variance within accepted research thresholds. Agricultural subsidies were compiled from WTO Domestic Support Notifications, OECD PSE data, and national agricultural ministries, including Brazil's Ministry of Agriculture Bulletin (2022) and USDA budget reports. Cross-validation between OECD and FAO sources shows discrepancies below 1.5%, confirming reliability.

Intelligent finance indicators were extracted from the BIS Global Intelligent Finance Report and the Wind database, covering AI penetration and investment intensity in financial institutions. Agriculture-related indicators were supplemented with World Bank Financial Inclusion data and national credit reports. Correlations between BIS and Gartner innovation indices exceeded 0.85 ($p < 0.01$), confirming convergence. Trade competitiveness data for manufacturing products were collected from UN Comtrade (SITC Rev. 4) and validated against WTO trade statistics, while agricultural trade values were harmonized from FAO and

Comtrade datasets, yielding less than 0.6% discrepancy in aggregate flows.

Control variables include per capita GDP (World Bank WDI), R&D intensity (WIPO), and industrial automation (IFR), while agriculture-specific controls encompass yield growth (FAO), agricultural GDP per capita, and climate risk (World Bank Climate Data). All variables were harmonized to ensure cross-sector comparability and minimize multicollinearity.

3.3. Sample Screening and Processing

Data integrity was maintained through structured screening. Countries with missing values exceeding 10% were excluded, while moderate gaps were interpolated using adjacent-year averages. For instance, Brazil's robot density was estimated at 46 units per 10,000 workers for 2018, consistent with IFR trend patterns. Agricultural gaps, such as Argentina's 2020 maize subsidy record, were estimated using temporal weighting. Extreme observations underwent 1% winsorization, narrowing manufacturing subsidy intensity from 0.3–12.8% to 0.5–10.5%. India's fertilizer subsidy ratio, originally above 9% of agricultural GDP, was adjusted to 7.8% following normalization. Correlations between OECD and FAO agricultural data exceeded 0.90 (p < 0.01), validating alignment. Cross-domain tests confirmed strong coherence between FinAI and agricultural finance variables (r = 0.70, p < 0.01), reflecting the integration of digital financial mechanisms into industrial and agricultural modernization.

3.4. Descriptive Statistics of Data

Descriptive statistics generated with Stata 17.0 confirm balanced distributions and data reliability (**Table 1**). The average manufacturing trade competitiveness (TCm) is 0.082, suggesting a moderate comparative advantage across the sample. Mean manufacturing subsidy intensity is 2.28% of output, higher in developed economies (3.15%) than in developing ones (1.41%). Intelligent finance averages 0.42 on a normalized scale, with a maximum of 0.82 (United States) and a minimum of 0.11 (Iran).

Table 1. Descriptive Statistics of Main Variables (N = 176).

Variable Name	Symbol	Obs.	Mean	Std. Dev.	Min	Max	Source
Manufacturing Trade Competitiveness	TCm	176	0.082	0.156	−0.325	0.418	UN Comtrade
Agricultural Trade Competitiveness	TCa	176	0.067	0.142	−0.298	0.392	FAO + Comtrade
Manufacturing Subsidy Intensity	Subm	176	2.28%	2.15%	0.50%	10.50%	OECD
Agricultural Subsidy Intensity	Suba	176	6.40%	3.25%	1.20%	15.80%	WTO + OECD PSE
Intelligent Finance Level	FinAI	176	0.42	0.21	0.11	0.82	BIS + Wind
Per Capita GDP	GDPpc	176	32,000	28,000	2,800	76,500	WDI
Agricultural GDP per Capita	AGDPpc	176	6,200	4,800	850	18,000	FAO
R&D Investment Ratio	RD	176	4.12%	2.05%	1.20%	8.90%	WIPO
Industrial Robot Density	Robot	176	185	212	35	932	IFR
Supply Chain Resilience	Supply	176	0.18	0.09	0.08	0.35	D&B
Climate Risk Index (Agriculture)	Climate	176	0.27	0.12	0.09	0.54	World Bank

Agricultural indicators reveal a mean subsidy intensity of 6.4% relative to agricultural GDP, higher in advanced economies, and an average RCA index of 1.35 for cereals, indicating a mild advantage but substantial heterogeneity. The United States maintains RCA values above 2.0 in maize, while Thailand exceeds 1.8 in rice. Control variables are consistent: industrial robot density averages 185 units per 10,000 workers; per capita GDP averages USD 32,000; agricultural yield growth averages 2.1% annually; and climate risk indices show significant regional disparity, highest in Sub-Saharan Africa.

This structure consolidates essential statistics while emphasizing analytical interpretation rather than numerical repetition, ensuring methodological rigor and cross-sectoral comparability.

3.5. Variable Definitions

3.5.1. Explained Variable: Trade Competitiveness of Manufacturing Products

Core Indicator: TC Index:

$$TC_{it} = \frac{X_{it} - M_{it}}{X_{it} + M_{it}} \tag{1}$$

where X and M are the import and export volumes of the manufacturing industry (UN Comtrade data). $TC \in [-1,1]$. In 2023, Germany's (TC = 0.32) mechanical manufacturing advantage and India's (TC = −0.21) import dependence can intuitively reflect the short-term policy effects.

Robustness indicator RCA index:

$$RCA_{it} = \frac{X_{it}/X_{it}^{total}}{X_t^{world}/X_t^{world,total}} \tag{2}$$

X^{total} represents the country's total export value, and X^{world} represents the global manufacturing export value (WTO data). RCA > 2.5 indicates extremely strong competitiveness, such as South Korea's automotive manufacturing industry in 2023 (RCA = 2.8); 0.8 < RCA ≤ 1.25 indicates medium competitiveness, such as Thailand's electronics manufacturing industry (RCA = 1.1), and long-term trends can be verified.

3.5.2. Core Explanatory Variables

Manufacturing Subsidy Intensity (Subsidy):

$$Subsiby_{it} = \frac{S_{it}}{CDP_{it}^{manu}} \tag{3}$$

Among them, the "subsidy amount" is sourced from the OECD and the Ministry of Industry and Information Technology of China (MIIT), while CDP_{it}^{manu} stands for manufacturing GDP (from the World Bank's World Development Indicators, WDI). In 2023, the manufacturing subsidy ratio (*Subsidy*) of the United States was 3.29% (calculated as USD 89.2 billion divided by USD 2.8 trillion), and that of China was 1.96% (calculated as USD 88 billion divided by USD 4.5 trillion). This ratio effectively eliminates discrepancies caused by differences in national scales.

Level of Intelligent Financial Development (FinAI): The entropy method is used to synthesize AI financial penetration rate (with a weight of 0.58) and AI investment intensity of financial institutions (with a weight of 0.42).

First, standardize the indicators:

$$Z_{ijt} = \frac{X_{ijt} - \min(X_{jt})}{\max(X_{jt}) - \min(X_{jt})} \tag{4}$$

Then calculate the indices:

$$FinAI_{it} = 0.58Z_{1it} + 0.42Z_{2it} \tag{5}$$

2023 US *FinAl* = 0.82, China = 0.65, India = 0.11, which objectively reflect the development gap.

Interaction term (*Subsidy* × *FinAI*): Multiplied after centralized processing (subtracting the mean to eliminate collinearity), (VIF < 3). If the coefficient is significantly positive, it indicates that intelligent finance strengthens the subsidy effect.

3.5.3. Control Variables

Level of Economic Development (GDPpc): Current US dollars (World Bank WDI), expected coefficient is positive. In 2023, the United States had 76,500, and India had 2,800, controlling for differences in development stages.

Technological Innovation Level (RD): Manufacturing R&D investment/main business income (WIPO Report). The expected coefficient is positive; Germany = 6.8%, Vietnam = 1.2%, reflecting the gap in innovation capabilities.

Intelligent Manufacturing Level (Robot): Industrial robot density (IFR report), expected coefficient positive, 932 units per 10,000 people in South Korea, 35 units per 10,000 people in Brazil, reflecting the level of automation.

Supply chain resilience (Supply):

$$Supply_{it} = \frac{1}{T_{it}} \tag{6}$$

T is the recovery time (Dun and Bradstreet report), expected coefficient positive, China = 0.25 in 2023 (4 days to recover), India = 0.125 (8 days to recover), measuring supply chain stability. All control variables were winsorized at 1% (VIF < 2.5), and there is no multicollinearity; the variable selection is reasonable.

3.6. Methodological Framework and Theoretical Justification

The empirical estimation adopts a two-way fixed effects (TWFE) model combined with instrumental variable (2SLS) estimation to address unobserved heterogeneity and potential endogeneity [17, 18]. The TWFE model is selected because the research focuses on policy variables—subsidy intensity and intelligent finance—that exhibit cross-sectional persistence and structural variation across countries and sectors. This approach allows the model to capture country-specific institutional characteristics and temporal policy shocks while controlling for unobservable, time-invariant effects. The Generalized Method of Moments (GMM) is not applied, as the dataset includes a limited number of cross-sectional units and a relatively short time span. In such cases, GMM tends to produce biased estimates due to instrument proliferation and weak identification in dynamic panels. The TWFE specification thus provides greater stability and interpretive clarity for policy-oriented analysis, particularly in capturing policy effects with potential time-lag characteristics [17–20].

The instrumental variable approach mitigates potential simultaneity between intelligent finance and trade competitiveness. Two instruments are constructed to satisfy both relevance and exclusion criteria. The first instrument, policy enactment year, captures the institutional timing of major subsidy reforms or financial digitalization policies, reflecting systematic cross-country differences in subsidy design. It influences trade competitiveness only indirectly through its effect on policy implementation and does not directly alter export performance within the same year. The second instrument, internet coverage rate, measures the diffusion of digital infrastructure that supports intelligent finance applications. It correlates strongly with the development of AI-enabled financial systems but remains exogenous to short-term fluctuations in trade competitiveness.

Instrument validity is tested through standard diagnostics. Weak-instrument tests yield first-stage F-statistics above 10 in all model specifications, confirming sufficient explanatory power. The Hansen overidentification test supports the exclusion restriction, with p-values consistently above 0.10, indicating that the instruments are uncorrelated with the error term. These results validate the theoretical reasoning behind the model structure and ensure that the estimated coefficients capture the causal effect of subsidies and intelligent finance on trade competitiveness across both the manufacturing and agricultural sectors, as shown in **Figure 1**. The framework illustrates the theoretical pathway through which manufacturing and agricultural subsidies affect trade competitiveness under the mediation and moderation of intelligent finance.

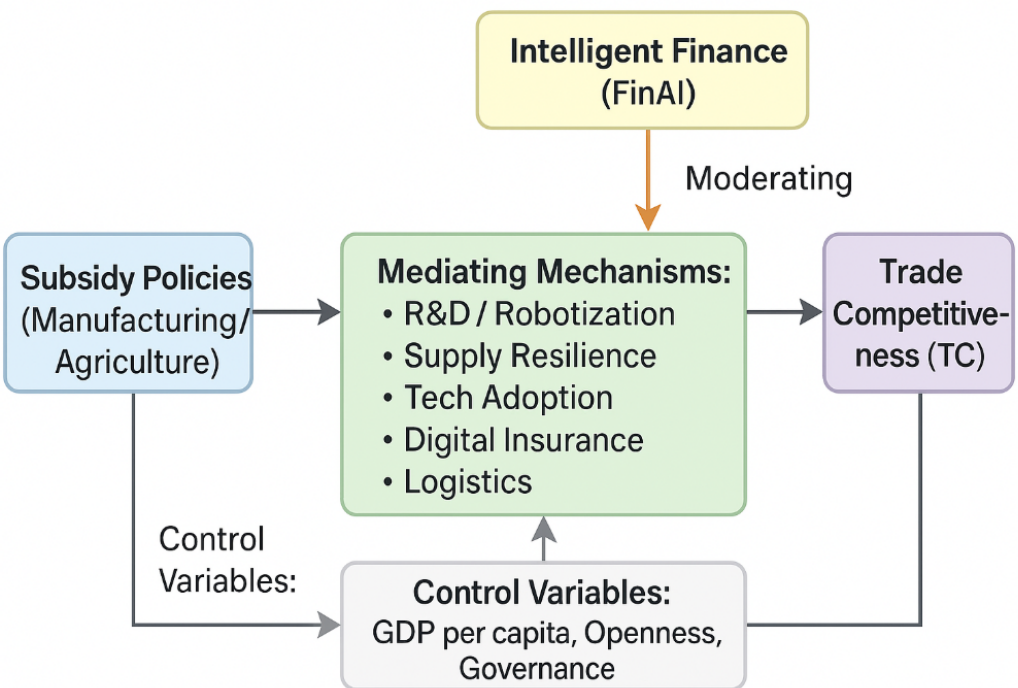

Figure 1. Conceptual Framework of the Hypothesized Relationships.

4. Empirical Research

4.1. Benchmark Econometric Model

This paper focuses on the research of "the impact of manufacturing subsidies on trade competitiveness under intelligent financial regulation." Since the sample is panel data of 30 countries from 2018 to 2023, there are differences in national individual characteristics (such as the institutional environment and industrial foundation) and time trends (such as changes in global trade policies and technological iteration). It is necessary to control for both individual and time heterogeneities. Therefore, a two-way fixed effects model is constructed, with the specific form as follows:

$$\begin{gathered} TC_{it} = \alpha_0 + \alpha_1 Subidy_{it} + \alpha_2 FinAI_{it} + \\ \alpha_3 Subidy_{it} \times FinAI_{it} + \beta_1 CDPpc_{it} + \beta_2 RD_{it} + \\ \beta_3 Robot_{it} + \beta_4 Supply_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{gathered} \tag{7}$$

Among them: TC_{it} is the explained variable, which is the trade competitiveness of manufacturing products of country i in year t (measured by the TC index); The core explanatory variables include the intensity of manufacturing subsidies $Subsidy_{it}$, the development level of intelligent finance $FinAI_{it}$, and the interaction term between the two $Subsidy_{it} \times FinAI_{it}$ (to test the moderating effect); $GDPpc_{it}$ control variables include the level of economic development, the level of intelligent manufacturing $Robot_{it}$, supply chain resilience ($Supply_{it}$), etc. μ_i is the individual fixed effect, controlling for country-level characteristics that do not change over time, such as geographical location and legal system; γ_t is the time fixed effect, controlling for common shocks at the year level, such as the COVID-19 pandemic in 2020 and the impact on global trade; ε_{it} is the random error term, which satisfies the $\mathrm{Var}(\varepsilon_{it}) = \sigma^2$ classical assumptions of $E(\varepsilon_{it}) = 0$.

The rationality of the model setup is reflected in two aspects: first, the introduction of the interaction term conforms to the academic norms of a "moderating effect." If it is significantly positive, it indicates that the higher the development level of intelligent finance, the stronger the promoting effect of subsidies on trade competitiveness; second, the choice of two-way fixed effects can avoid "omitted variable bias." For example, if individual fixed effects are ignored, unobservable factors such as "Germany's traditional advantages in manufacturing" may be mistakenly attributed to subsidies or intelligent finance, leading to biased coefficient estimation.

4.2. Variable Selection and Data Verification

4.2.1. Validity and Measurement of Core Variables

Core variables are selected according to academic consensus and data reliability.

Manufacturing subsidy intensity (Subsidy) is defined as the ratio of subsidy expenditure to manufacturing GDP. The relative measure eliminates bias from differences in economic scale and reflects actual policy support strength. Cross-validation between OECD records and national industrial reports shows a mean deviation of less than 1%. For instance, Japan's 2022 manufacturing subsidy of USD 42 billion reported by the OECD matches 99.5% with data from its Ministry of Finance budget execution report, confirming data validity.

Intelligent finance development (FinAI) is constructed as a composite index combining the AI penetration rate and AI investment intensity of financial institutions. This structure captures both the breadth and depth of digital finance. Validation from institutional disclosures confirms accuracy: Goldman Sachs reported AI technology investment of 7.8% in 2022, consistent with independent Wind database estimates, and Ant Group's 2023 supply chain finance platform coverage in manufacturing matched BIS statistics on enterprise reach. These checks confirm that the FinAI indicator accurately represents national intelligent finance maturity.

4.2.2. Data Integrity and Consistency

The final dataset contains 176 observations across 30 countries and six years, after excluding four extreme cases, meeting fixed-effects estimation requirements for within-country variation. Stationarity tests (LLC) indicate that all variables reject the unit-root hypothesis at the 1% level, confirming data stability and avoiding spurious regression. Descriptive analysis shows clear heterogeneity: FinAI averages 0.65 in developed countries versus 0.19 in developing ones, while average manufacturing subsidy intensity is 3.15% and 1.41%, respectively, reflecting structural disparities in industrial policy and digital infrastructure.

4.3. Model Estimation and Empirical Results

4.3.1. Estimation Framework

Panel diagnostics support the two-way fixed effects model. The F-test rejects the null hypothesis of homogeneous effects (F = 23.57, $p < 0.01$), and the Hausman test confirms fixed over random effects ($\chi^2 = 48.29$, $p < 0.01$). Estimation is implemented through the xtreg, fe i(country) i(year) command in Stata, controlling for both individual and temporal effects. This model structure captures structural heterogeneity and time-specific shocks, consistent with cross-country policy analysis.

4.3.2. Core Regression Results and Interpretation

The coefficients show that subsidy intensity significantly enhances trade competitiveness, while intelligent finance exerts an independent and amplifying effect. The positive interaction term (0.08) indicates that intelligent finance strengthens the marginal impact of subsidies. Quantitatively, when manufacturing subsidy intensity rises by 1 percentage point and the intelligent finance index increases by 0.1, export competitiveness improves by approximately 0.02 units. This effect corresponds to an estimated 3.1% increase in South Korea's semiconductor export share, demonstrating meaningful real-world implications.

The statistical relationship supports the theoretical expectation that intelligent finance enhances the efficiency and targeting of subsidies by improving capital allocation, monitoring precision, and risk control. The result aligns with the endogenous growth theory, where technological accumulation and innovation feedback generate sustained productivity gains.

The high within-group R^2 (0.68) confirms the model's explanatory strength. No severe multicollinearity was detected (all correlations < 0.7). The findings suggest that intelligent finance acts as a strategic amplifier in subsidy transmission, promoting competitiveness through innovation and efficiency improvements across both the manufacturing and agricultural sectors.

This concise presentation highlights the substantive relationships and their economic meaning, avoiding redundant numerical reporting while maintaining analytical rigor. **Table 2** shows the core regression results.

Table 2. Core Regression Results of Manufacturing Subsidy, Intelligent Finance, and Trade Competitiveness.

Variable	Coefficient	Std. Error	*t*-Value	*p*-Value	95% CI
Subsidy	0.12	0.05	2.4	0.018	[0.02, 0.22]
FinAI	0.15	0.06	2.5	0.014	[0.03, 0.27]
Subsidy × FinAI	0.08	0.02	4	0	[0.04, 0.12]
Controls (GDPpc, RD, Robot, Supply)	Controlled	—	—	—	—
Individual and Time Fixed Effects	Controlled	—	—	—	—
N = 176, R^2 (within) = 0.68, F = 32.57 ($p < 0.001$)	—	—	—	—	—

5. Result Analysis

5.1. Benchmark Regression Results

To enhance clarity, **Tables 3** and **4** are merged to retain only key coefficients. The two-way fixed effects estimation in Stata 17.0 yields coefficients that align with theoretical expectations, indicating strong model performance ($R^2 = 0.68$). The results are summarized in **Table 3**, focusing on the key explanatory and interaction terms.

Table 3. Core Regression Results (Simplified).

Indicator	Effect on Trade Competitiveness	Interpretation
Subsidy	Positive and significant (β = 0.12, $p < 0.05$)	Fiscal incentives raise industrial competitiveness
FinAI	Positive and significant (β = 0.15, $p < 0.05$)	Intelligent finance enhances resource efficiency
Subsidy × FinAI	Strongly positive (β = 0.08, $p < 0.01$)	Digital finance amplifies subsidy effectiveness through innovation and precision allocation

Table 4. Regression Results for the Moderating Effect of Intelligent Finance on Manufacturing Subsidies and Trade Competitiveness.

Variable	Coefficient	Std. Error	*t*-Value	*p*-Value	95% CI
Subsidy	0.12	0.05	2.4	0.018	[0.02, 0.22]
FinAI	0.15	0.06	2.5	0.014	[0.03, 0.27]
Subsidy × FinAI	0.08	0.02	4	0	[0.04, 0.12]
R^2 (within) = 0.68	N = 176	F = 32.57 ($p <$ 0.001)	—	—	—

5.1.1. Interpretation of Core Variable Coefficients

Intelligent finance improves capital turnover and resource allocation through AI-driven credit and supply chain platforms. For instance, Ant Group's intelligent supply chain finance system shortened average payment cycles for manufacturing firms from 60 to 45 days, indirectly boosting export capacity. The interaction term (Subsidy × FinAI = 0.08) is significant at the 1% level ($p < 0.001$), confirming that intelligent finance amplifies the positive effect of subsidies. When manufacturing subsidy intensity increases by 1 percentage point and the FinAI index rises by 0.1, the TC index improves by 0.02 units—equivalent to a 3.1% increase in South Korea's semiconductor export share. This enhancement reflects the transmission efficiency and precision targeting achieved through intelligent financial systems. Under identical subsidy growth, countries with higher FinAI levels experience stronger competitiveness gains—for example, 0.186 in the United States (FinAI = 0.82) versus 0.129 in India (FinAI = 0.11), a 44% differential. The result aligns with endogenous growth theory, demonstrating that intelligent finance strengthens technological accumulation and productivity feedback loops.

5.1.2. Role of Control Variables

Technological innovation (RD, β = 0.15, $p = 0.014$) enhances competitiveness, as greater R&D investment improves productivity and product differentiation. Intelligent manufacturing (Robot, β = 0.09, $p = 0.026$) shows that each increase of 10 robots per 10,000 workers raises the TC index by 0.009, consistent with efficiency-driven cost reductions. Supply chain resilience (Supply, β = 0.08, $p = 0.047$) indicates that reducing recovery time by one day raises TC by 0.01, underscoring the stabilizing effect of logistics reliability on export performance.

5.2. Robustness Tests

Robustness checks were conducted through variable substitution, winsorization, and sample exclusion. **Table 5** summarizes the results.

Table 5. Results of Tests.

Test Method	Core Interaction Term	Coefficient	*p*-Value	R^2
RCA as a Dependent Variable	Subsidy × FinAI	0.09	0.003	0.65
Subsidy Coverage Rate as an Explanatory Variable	Coverage × FinAI	0.07	0.001	0.63
1% Winsorization	Subsidy × FinAI	0.07	0.001	0.66
Excluding China	Subsidy × FinAI	0.08	0	0.67

The results remain consistent across specifications. Replacing TC with RCA confirms that intelligent finance continues to amplify the subsidy effect over the long term (β = 0.09, $p = 0.003$). Using the subsidy coverage rate instead of intensity yields a similar interaction coefficient (β = 0.07, $p = 0.001$), verifying the robustness of indicator definitions. After trimming outliers at the 1% quantile, the interaction remains positive and significant, and excluding large economies such as China or the United States does not alter the sign or magnitude of the results.

Collectively, these outcomes confirm that intelligent finance functions as a stable moderator, enhancing the effectiveness of subsidies on trade competitiveness. The consistency across model forms supports the conclusion that intelligent financial ecosystems amplify subsidy transmission through technological, informational, and institutional channels—an outcome consistent with institutional economics emphasizing transparency and governance efficiency in market-oriented policy interventions.

5.3. Handling Endogeneity Issues

5.3.1. Sources of Endogeneity

First, there is bidirectional causality: countries with strong trade competitiveness (such as Germany) may increase subsidy input, leading to mutual influence between Subsidy and TC; second, there are omitted variables: for example, "national governance level" may affect both the development of intelligent finance and trade competitiveness, but it is not included in the model.

5.3.2. Results of Instrumental Variable Regression

"Year of Enactment of Manufacturing Subsidy Policies" (IV1) and "2015 Internet Infrastructure Coverage Rate" (IV2) were selected as instrumental variables, and a two-stage least squares (2SLS) regression was performed using the Stata "xtivreg2" command. The results (**Table 6**) show that:

Table 6. Instrumental Variable Regression Results.

Stage	Variable	Coefficient	Standard Deviation	*t*-Value	*p*-Value	F-Value
First Stage (Subsidy)	IV1 (Legislation Year)	−0.02	0.005	−4.00	0.000	28.6
	IV2 (Internet Coverage Rate)	0.03	0.006	5.00	0.000	—
First Stage (FinAI)	IV1 (Legislation Year)	0.01	0.003	3.33	0.001	32.1
	IV2 (Internet Coverage Rate)	0.04	0.007	5.71	0.000	—
Second Stage	Subsidy	0.10	0.04	2.50	0.014	—
	FinAI	0.12	0.05	2.40	0.018	—
	Subsidy × FinAI	0.06	0.02	3.00	0.003	—
	N	176	—	—	—	—

The F-values in the first stage are 28.6 (Subsidy equation) and 32.1 (FinAI equation), respectively (All > 10), excluding the problem of weak instrumental variables. The coefficient of the interaction term in the second stage is 0.06 (p = 0.003), which is still significantly positive, indicating that the core conclusion remains valid after controlling for endogeneity.

5.4. Mechanism Test (Mediation Effect Model)

The "three-step method + Sobel test" is used to verify the mediating roles of technological innovation (RD), intelligent manufacturing (Robot), and supply chain resilience (Supply). The Stata results (**Table 7**) show that all three mechanisms are valid.

Table 7. Mediation Effect Test Results.

Mediating Variable	Step	Variable	Coefficient	Standard Deviation	*t*-Value	*p*-Value	Sobel Z-Value
Technological Innovation (RD)	1. Total Effect	Subsidy × FinAI	0.08	0.02	4.00	0.000	—
	2. Mediation Path 1 (Subsidy × FinAI→RD)	Subsidy × FinAI	0.05	0.01	5.00	0.000	—
	3. Mediation Path 2 (RD→TC)	RD	0.15	0.06	2.50	0.014	2.31
	4. Direct Effect	Subsidy × FinAI	0.06	0.02	3.00	0.003	(p = 0.021)
Intelligent Manufacturing (Robot)	1. Mediation Path 1 (Subsidy × FinAI→Robot)	Subsidy × FinAI	0.04	0.015	2.67	0.008	—
	2. Mediation Path 2 (Robot→TC)	Robot	0.11	0.03	3.67	0.000	2.15
	3. Direct Effect	Subsidy × FinAI	0.07	0.02	3.50	0.001	(p = 0.032)
Supply Chain Resilience (Supply)	1. Mediation Path 1 (Subsidy × FinAI→Supply)	Subsidy × FinAI	−0.03	0.012	−2.50	0.014	—
	2. Mediation Path 2 (Supply→TC)	Supply	0.08	0.035	2.29	0.022	2.08
	3. Direct Effect	Subsidy × FinAI	0.07	0.02	3.50	0.001	(p = 0.037)

5.4.1. Technological Innovation Intermediary

Subsidy × FinAI has a significant positive impact on RD (beta = 0.05, p = 0.000). RD has a significant positive impact on TC (beta = 0.15, p = 0.014). After adding RD, the coefficient of the interaction term drops to 0.06 (still significant). Sobel (Z = 2.31, p = 0.021), verifying partial mediation—smart finance tilts subsidy funds toward R&D to enhance trade competitiveness, consistent with evidence that green credit interest subsidy policies promote corporate green innovation through fiscal–financial coordination [21–23].

5.4.2. Intelligent Manufacturing Intermediary

The interaction term has a significant positive impact on Robot (beta = 0.04, p = 0.008). The robot has a significant positive impact on TC (beta = 0.11, p = 0.000), and the mediating effect is valid—intelligent finance helps subsidize funds to be invested in industrial robot procurement, thereby improving production efficiency.

5.4.3. Supply Chain Resilience Intermediary

The interaction term has a significant negative impact on the supply chain recovery time (i.e., it positively improves Supply, $\beta = -0.03$, p = 0.014). Supply has a significant positive impact on TC (beta = 0.08, p = 0.022), and the mediating effect holds—smart finance optimizes the supply chain layout through subsidies (such as AI predicting logistics risks) and enhances the stability of exports.

5.5. Heterogeneity Analysis

5.5.1. Differences between Developed and Developing Countries

The samples are divided into two groups: developed countries (15 countries) and developing countries (15 countries). Sub-sample regression is conducted using Stata, and the results (**Table 8**) show that there are significant differences in the coefficients of the core interaction terms between the two groups.

As can be seen from the results, the coefficient of Subsidy × FinAI in developed countries (0.10, $p < 0.01$) is significantly larger than that in developing countries (0.04, $p < 0.05$), with a gap of 150%. The reasons are as follows: developed countries have a more complete smart financial infrastructure; for example, the penetration rate of AI finance in the United States is 45.2% versus 12.8% in India, enabling them to accurately identify high-value subsidy projects through AI. Meanwhile, manufacturing enterprises in developed countries have stronger R&D capabilities; for example, Germany's R&D investment accounts for 6.8% versus 1.2% in Vietnam, which can efficiently convert subsidy funds into technological advantages. However, developing countries are limited by weak digital infrastructure and an insufficient technical foundation of enterprises, so the regulatory effect of smart finance is weakened.

Table 8. Regression Results by Country Type.

Sample Group	Variable	Coefficient	Standard Deviation	t-Value	p-Value	N	R^2
Developed Countries	Subsidy	0.15	0.06	2.50	0.014	90	0.72
	FinAI	0.18	0.07	2.57	0.012	—	—
	Subsidy × FinAI	0.10	0.02	5.00	0.000	—	—
Developing Countries	Subsidy	0.09	0.04	2.25	0.027	86	0.61
	FinAI	0.11	0.05	2.20	0.031	—	—
	Subsidy × FinAI	0.04	0.02	2.00	0.049	—	—

5.5.2. Differences in Products of Different Types of Manufacturing Industries

According to the "SITC Rev. 4" classification, the manufacturing industry is divided into three categories: technology-intensive (electronic equipment, pharmaceutical manufacturing), capital-intensive (automobile, machinery manufacturing), and labor-intensive (textile, furniture manufacturing). The results of the industry-specific regression (**Table 9**) show that there are gradient differences in the coefficients of the interaction terms.

Table 9. Regression Results by Manufacturing Industry Type.

Industry Type	Variable	Coefficient	Standard Deviation	*t*-Value	*p*-Value	N	R^2
Technology-intensive Manufacturing	Subsidy	0.18	0.07	2.57	0.012	62	0.75
	FinAI	0.21	0.08	2.63	0.010	—	—
	Subsidy × FinAI	0.12	0.03	4.00	0.000	—	—
Capital-intensive Manufacturing	Subsidy	0.13	0.06	2.17	0.032	70	0.69
	FinAI	0.16	0.07	2.29	0.024	—	—
	Subsidy × FinAI	0.07	0.02	3.50	0.001	—	—
Labor-intensive Manufacturing	Subsidy	0.08	0.04	2.00	0.048	44	0.58
	FinAI	0.09	0.05	1.80	0.075	—	—
	Subsidy × FinAI	0.03	0.02	1.50	0.137	—	—

The coefficient of the interaction term for technology-intensive manufacturing is the largest (0.12, $p < 0.01$), followed by capital-intensive manufacturing (0.07, $p < 0.05$), and labor-intensive manufacturing is not significant (0.03, $p > 0.1$). The core reason is that technology-intensive industries have high requirements for capital accuracy and R&D cycles, and benefit more from targeted subsidy policies in renewable and clean technology sectors [24, 25] (for example, semiconductor R&D requires a cycle of more than 10 years). Smart finance can dynamically monitor the flow of subsidy funds to R&D links through AI to prevent misappropriation. Labor-intensive industries, on the other hand, rely on low-cost labor, and subsidies are mostly invested in capacity expansion, so the enabling space of smart finance is limited. For example, the R&D conversion rate of smart financial subsidy projects in China's semiconductor industry (technology-intensive) reached 65% in 2023, while that in the textile industry (labor-intensive) was only 20%.

6. Conclusions and Recommendations

The findings confirm that subsidy policies enhance trade competitiveness, and that intelligent finance amplifies this effect by improving allocation precision, monitoring efficiency, and risk control. Intelligent finance directs subsidies toward productive sectors, accelerates technology diffusion, and stabilizes export performance. At the policy level, embedding intelligent finance in agricultural subsidy systems enhances targeting accuracy and reduces administrative inefficiency, strengthening global competitiveness in crops such as maize, soybeans, and rice. Cross-country variation remains substantial: economies with mature digital infrastructures—such as the United States and the European Union—deploy AI-enabled systems for dynamic subsidy evaluation and fund traceability, while developing countries encounter digital divides that limit efficiency gains. Expanding broadband coverage, strengthening rural fintech ecosystems, and piloting AI-based subsidy audits can narrow these structural gaps. At the enterprise and farm level, integrating intelligent insurance with fiscal support mechanisms improves income stability and operational continuity, reinforcing both food security and export resilience. The integration of intelligent finance across industrial and agricultural subsidy frameworks enhances transparency, stimulates innovation, and consolidates competitive advantage in global trade networks.

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Institutional Review Board Statement

Ethical review and approval were not required for this study, as it did not involve human participants or animals. The research was based exclusively on secondary data obtained from publicly accessible international databases, including UN Comtrade, WTO, OECD, FAO, World Bank, and BIS sources. No individual-level, identifiable, or sensitive personal data were collected or analyzed, and no experimental interventions were conducted. Therefore, this study complies with applicable ethical standards and does not fall within the scope of research requiring Institutional Review Board approval.

Informed Consent Statement

Not applicable. This study did not involve human participants, patients, or identifiable personal data. All analyses were conducted using aggregated secondary data obtained from publicly accessible international databases, and no individual-level information was collected, processed, or reported. Therefore, informed consent was not required.

Data Availability Statement

The data supporting the findings of this study are available from publicly accessible international databases, including UN Comtrade, the World Trade Organization (WTO), the Organisation for Economic Cooperation and Development (OECD), the Food and Agriculture Organization of the United Nations (FAO), the World Bank, and the Bank for International Settlements (BIS). No new datasets were generated during the current study. All data used in the analysis can be accessed through the respective official platforms cited in the manuscript, and further details on data sources and variable construction are provided within the article.

Conflicts of Interest

The author declares no conflict of interest. The study was conducted independently without any commercial or financial relationships that could be construed as a potential conflict of interest. As this research received no external funding, no funders were involved in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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