

Article

Research on the Impact of the Development of China's Digital Trade on the International Competitiveness of the Manufacturing Industry

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Abstract: The world is currently experiencing an unprecedented period of disruption. Traditional theories of comparative advantage can no longer serve as the sole drivers for enhancing the international competitiveness of China's manufacturing industry. In this new era, the future development of China's manufacturing industry has become a pressing issue that demands immediate attention. With the rapid advancement of next-generation digital technologies and information and communication technologies, global digital trade has surged, emerging as a key engine of economic growth for countries worldwide. This trend undoubtedly presents new opportunities and platforms for strengthening the international competitiveness of China's manufacturing industry. How China's manufacturing industry can effectively leverage digital trade to secure a competitive advantage amid intensifying global competition has become a critical and urgent area of research. Using panel data from 31 provinces, autonomous regions, and municipalities in China spanning from 2012 to 2022, this study develops a comprehensive evaluation framework for digital trade and manufacturing competitiveness. It empirically investigates the impact and mechanisms through benchmark regression models, mediation effect models, and spatial econometric models. The findings reveal that digital trade has a significant positive impact on the international competitiveness of China's manufacturing industry. The effect of digital trade on competitiveness is most pronounced in the eastern region and least evident in the western region. Additionally, foreign direct investment and technological research and development capabilities are found to indirectly enhance the international competitiveness of the manufacturing industry. Furthermore, digital trade exhibits spatial spillover effects, wherein improvements in manufacturing competitiveness within one province positively influence neighboring provinces. This study offers valuable theoretical and policy implications for evaluating the impact of digital trade on the international competitiveness of manufacturing and strategies for enhancing it.

Keywords: digital trade; international competitiveness of the manufacturing industry; impact mechanisms; spatial measurement



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1. Introduction

Global manufacturing is undergoing a period of profound transformation. Relying on traditional comparative advantages is no longer sufficient to enhance the international competitiveness of the manufacturing industry in the new era. China's manufacturing industry is characterized by being "large but not strong, and comprehensive but not resilient", which remains a significant challenge. Enhancing the international competitiveness

of the manufacturing industry is critical for China to strengthen its national power and achieve high-quality economic development [1]. Driven by the rapid growth of the digital economy and the transformation of traditional industries, digital trade, a new form of trade enabled by digital technology, has facilitated trade, reduced information asymmetry, and lowered trade costs. These advantages have triggered a profound transformation in how manufacturing is organized, fostering the development of service-oriented and digitalized manufacturing industries. Moreover, the rapid development of digital trade has provided new momentum for the manufacturing industry, improving its international competitiveness and offering an opportunity for Chinese manufacturers to advance to the middle range or high end and catch up with global competitors [2]. Additionally, the manufacturing industry plays a critical role in reducing carbon emissions and achieving carbon neutrality. As part of implementing ESG goals, Chinese manufacturing companies should emphasize the role of digital technology innovation. They should integrate the “green + intelligent manufacturing” development concept with ESG principles, encouraging the entire manufacturing supply chain to prioritize environmental governance, adopt innovation-driven development, and improve digital technology and product quality. Therefore, as a leading manufacturing country, China should seize the rare historical opportunity presented by digital trade. It should continuously introduce high-end services, better utilize advanced foreign service production factors, and leverage digitalization to foster high-quality development, remove bottlenecks in the domestic economic cycle, and enhance the international competitiveness of its manufacturing industry. The relationship between digital trade and manufacturing has been extensively studied by scholars. Currently, research primarily focuses on the definition, characteristics, and measurement of digital trade; the assessment of the international competitiveness of the manufacturing industry, and the role of digital trade in its development. The existing literature provides a crucial foundation for constructing a comprehensive evaluation framework for digital trade and the international competitiveness of the manufacturing industry. However, empirical research in this field remains limited, and further studies are needed to bridge the gap between theory and practice and deepen our understanding of the impact of digital trade on the manufacturing industry. Given this context, this paper will focus on the manufacturing industry, combining qualitative and quantitative analysis to theoretically explore and empirically test the impact of digital trade on its international competitiveness. The expected contributions are as follows: First, the paper uses the entropy method to construct a comprehensive evaluation framework with five dimensions: the foundation of digital trade, the digital technology environment, the potential of digital trade, the capacity of digital trade, and the digital trade industry. Then, the coefficient of variation method is used to assign weights and calculate the comprehensive index of international competitiveness of the manufacturing industry. Second, based on the platform-based, digitalized, intelligent, and inclusive characteristics of digital trade, factors such as digital platforms, digital technology, and capital are introduced to construct a theoretical system of mechanisms for enhancing the international competitiveness of the manufacturing industry through digital trade, providing a theoretical basis for further research on the international competitiveness of the manufacturing industry. Third, it verifies the non-linear impact of digital trade on the international competitiveness of the manufacturing industry, correctly characterizes the relationship between digital trade and the international competitiveness of the manufacturing industry, and provides a theoretical reference for formulating relevant industrial policies.

2. Literature Review

2.1. Research on Digital Trade

Currently, there is no internationally agreed-upon definition of “digital trade” or standardized statistical framework. This lack of consensus stems primarily from the challenge of delineating a clear boundary for the scope of digital trade, which highlights the limitations of existing classification systems in accurately identifying and distinguishing it. Scholars generally hold two distinct perspectives on the concept of digital trade: a narrow definition and a broader interpretation. The early definitions of digital trade were narrow in scope, with the subject matter limited to digital products and services. Weber (2010) defines digital trade as commercial activities that use the Internet and other electronic means to deliver valuable products or services [3]. Xiong et al. (2011) define digital trade as a business model based on the Internet and digital exchange technology that provides the digital electronic information required for interaction between suppliers and demanders and enables digital information to be the subject of trade [4]. In July 2013, the US International Trade Commission, in its report “Digital Trade in the US and Global Economy (I)”, limited the scope of digital trade to digital products and services, excluding physical goods [5]. However, the report “Digital Trade in the United States and Global Economy (II)” released in August 2014 emphasized the role of the Internet and appropriately broadened the scope of digital trade [6]. In August 2017, the US International Trade Commission once again defined “digital trade”, emphasizing that the mode of delivery of digital trade should be “digital delivery”, thus excluding most physical goods [7]. In March 2019, the OECD, WTO, and IMF released the *Digital Trade Measurement Manual*, resulting in a broad definition of digital trade. It proposes that digital trade consists of “digitally ordered” and “digitally delivered” goods [8]. Compared with the “narrow definition”, this definition covers more entities or goods that are traded digitally through information and communication technology (ICT). In the “White Paper on the Development and Impact of Digital Trade (2020)”, the China Academy of Information and Communications Technology defines digital trade as a form of trade in which digital technology plays an important role [9]. The most significant difference between digital and traditional trade lies in digitizing trade methods and trading partners. This development arises from innovations based on international frameworks for identifying digital trade. Specifically, the digitization of trade methods refers to the integration of digital technologies into international trade processes, resulting in transformations such as digital coordination, digital ordering, digital delivery, and digital settlement. Meanwhile, the digitalization of trade objects involves the conversion of elements, products, and services into data forms, which have become essential trade commodities. This shift extends the international division of labor from the physical world into the digital realm.

With the continuous updating and development of digital technology, digital trade, as the highest form of evolution of international trade in the digital age, has changed the original objects and methods of trade [10]. Compared with traditional trade, digital trade reflects new characteristics regarding trade motivation, mode, structure, trade objects, trade subjects, trade and division of labor organization forms, and trade supervision requirements [11]. From digital delivery to digital connection, it promotes larger-scale physical trade and effectively reduces information asymmetry in the trading process [12]. Digital trade has an advantage in reducing costs and increasing efficiency. Adopting more innovative methods helps companies save money and labor and reduce costs in all aspects of the enterprise, from supply chain to after-sales service, i.e., search costs, information costs, contract costs, supervision costs, data storage costs, and especially logistics costs [13], thereby improving production efficiency and enhancing enterprise competitiveness [14–17].

The measurement of digital trade statistics has always concerned policymakers and researchers in related fields. The main obstacle to measuring digital trade is the lack of an internationally recognized conceptual framework. As the connotation and denotation of digital trade have become more developed, two measurement methods corresponding to narrow and broad definitions have also been developed. One is based on the “narrow-caliber” concept of digital trade and is the “Grimm measurement method” proposed by American business expert Grimm (2016) [18]. The other is from the *Digital Trade Measurement Manual* jointly released by the OECD, WTO, and IMF [8], which proposes a more feasible general method for measuring digital trade based on the broad-caliber conceptual framework and is known as the “OECD–WTO–IMF measurement method”. In addition, Chinese scholars Jia et al. (2021) proposed the “dual-core–three-ring” conceptual framework for digital trade, constructed an indicator system for measuring the scale of digital trade, and developed a digital trade measurement method with the “actual digital delivery ratio” as the key [19]. Ma et al. (2022) constructed an evaluation index system for the development potential of digital trade powers from the dimensions of trade potential, digital market, digital trade structure, digital trade status, and digital trade environment [20]. They evaluated the development of digital trade in 59 countries. Other scholars constructed a digital trade index evaluation system based on digital trade data from 49 major global economies from 2014 to 2020. They used the entropy weight method to calculate the weight and applied descriptive statistical analysis and kernel density estimation methods to characterize the dynamic evolution of digital trade development in various countries [21]. Some scholars have also constructed evaluation indicators for the development level of digital trade, including five first-level indicators and fifteen s-level indicators: digital infrastructure, digital technology level, industrial digital trade level, digital industrial trade level, and trade potential [22]. Research on the measurement of digital trade is still in its infancy. However, it is firmly believed that as new trading parties and international digital trade measurement experiences continue to emerge, digital trade measurement methods will continue to be updated and refined.

2.2. Research on the International Competitiveness of the Manufacturing Industry

Research on the international competitiveness of the manufacturing industry focuses mainly on the measurement of indicators, influencing factors, and ways to improve. First, the measurement indicators of the international competitiveness of the manufacturing industry are constructed from multiple perspectives to assess the development of the international competitiveness of the manufacturing industry more systematically and comprehensively and thus more effectively promote its improvement. In international research on the measurement of the international competitiveness of the manufacturing industry, the diamond model was the first and most widely used to assess industrial competitiveness [23]. Scholars used the ECM model to analyze the international competitiveness of the Czech manufacturing industry using data from 13 manufacturing sub-sectors from 1995 to 2011 [24]. Using macroeconomic factors and business environment indicators that may impact a country’s competitiveness, an appropriate indicator evaluation system was established to analyze and study the main economic factors affecting the competitiveness of Central and Eastern European countries [25]. In addition, scholars used data from the United Nations Commodity Trade Statistics Database (UN Comtrade) to calculate comparative and competitive advantage indices for manufactured goods [26]. In order to ensure the objectivity and scientific nature of the results, other scholars have used multiple industrial competitiveness indicators to comprehensively measure the international competitiveness of the manufacturing industry from multiple perspectives [27] or have analyzed the competitiveness of China’s manufacturing industry using similar indicators [28].

With the rapid development of high-quality industries, it is essential to study the sustainable competitiveness of the manufacturing industry and its influencing factors. Many scholars have conducted empirical analyses of the various factors that affect the sustainable competitiveness of the manufacturing industry. The research results show that information technology is vital in all countries, but it is more effective in developed countries [29]. Empirical tests using panel data on China's manufacturing industry also confirm that informatization significantly impacts the efficiency of technological innovation in China's industry [30]. Moreover, the improvement of the comprehensive quality of FDI has a positive effect on breakthrough innovation by local enterprises. In terms of sub-characteristics, the positive effect of FDI with a high level of openness and a high level of social contribution is the most significant [31], and the negative impact of foreign investment access restrictions on manufacturing export competitiveness is greater than the positive impact of opening up trade in services [32]. Third, innovation not only improves the competitiveness of the manufacturing industry but also promotes the sustainable development of traditional manufacturing industries [33]. Independent innovation is the basis for enhancing the international competitiveness of industries, and open innovation is a critical path. The higher the degree of openness, the more significant the impact of independent research and development investment on industrial competitiveness [34,35]. In addition, industrial spatial correlation is increasingly likely to occur among members with similar levels of economic or trade openness. Some scholars have concluded from spatial econometric model analysis that the international competitiveness of manufacturing among network members is affected differently by the level of foreign trade openness, the utilization rate of free trade zone preferences, the stringency of rules of origin, and external shocks based on different spatial correlation rules [36].

In order to further enhance the international competitiveness of China's manufacturing industry, scholars propose continuing to expand and open up to the outside world, enhancing the level of regional integration, and adhering to innovation-driven economic development from the perspective of domestic technological content [37]. It is also recommended to strengthen domestic investment in research and development and human capital, strengthen the leading position of state-owned capital in technological catch-up and talent cultivation, independently overcome core technologies, reduce external dependence on technology and critical components, improve the technological content and added value of manufacturing export products, save energy and reduce emissions, and rely on technology and efficiency to improve the quality of manufacturing development [38] and to continuously expand the comprehensive competitive and cooperative advantages formed by labor factors, open cooperation, infrastructure and industrial support, large-scale markets, and technological innovation [39]. Moreover, while continuously improving the independent innovation capabilities of the manufacturing industry, special attention should be paid to enhancing the fit between the digital economy and technological innovation, rapidly improving the international competitiveness of China's manufacturing industry, and achieving high-quality development of the industry [40]. These research conclusions are of great theoretical and practical value for analyzing and understanding the competitiveness of the manufacturing industry.

2.3. Research on the Relationship Between Digital Trade and the International Competitiveness of the Manufacturing Industry

Initially, scholars, both domestic and international, focused on the impact of the Internet and information technology on the export competitiveness of the manufacturing industry. As informatization became the mainstream trend, scholars found that digital communication infrastructure is essential in reducing trade costs, promoting economies of scale, and facilitating knowledge accumulation [41]. Moreover, by measuring the con-

centration of various sub-sectors in China's manufacturing industry, the dominant force behind the internetization of manufacturing sub-sectors was proposed [42]. It was also verified that the development of the Internet has cost-saving effects on manufacturing exports and enhances human capital [43]. The development of the Internet is considered one of the most critical factors influencing a country's manufacturing innovation capacity and international competitiveness [44].

With the deepening of research, digital trade, as an emerging form of trade in the context of globalization, is reshaping the global economic landscape. In particular, in the manufacturing industry, scholars have found that the development of digital technologies not only promotes cross-border e-commerce and the digitization of supply chains but also influences export structures and industrial competitiveness to varying degrees.

(1) The Impact of Digital Trade on Export Structures

Digital trade, by facilitating the digitization of products and services, enables businesses to exchange a broader range of goods across borders via online platforms, thereby influencing export structures. Recent studies have extensively examined the significant effects of digital trade on export product categories, market distribution, and trade modalities. First, digital trade has led to a more diversified export structure. With the application of digital technologies, traditional export products (such as raw materials and primary processed goods) are gradually being replaced by digital goods (such as software, digital design, and creative content) [45]. This change allows developing countries to export higher value-added goods, no longer relying solely on low-cost manufacturing and raw material exports. Furthermore, digital trade helps small businesses and emerging markets integrate into global value chains, enabling them to export a broader range of products, especially high-tech goods that were traditionally difficult to export [46]. Second, digital trade has significantly affected the distribution of export markets. Tu et al. (2018) found that with the rise of cross-border e-commerce platforms, export markets are no longer limited to the major consumer countries of bulk commodities; more small and medium-sized economies can break geographic and cultural barriers through digital trade and enter new markets [47]. This shift has led to a more balanced export market structure, particularly in regions such as Southeast Asia, Africa, and Latin America, where digital platforms have greatly facilitated the globalization of local enterprises. Moreover, López-González et al. (2018) emphasized that digital trade has driven the growth of service trade, especially high-value-added digital services (such as software development, cloud computing services, and digital design), which have become a new driving force for exports [12]. Traditional manufacturing countries, such as China and India, are increasingly relying on digital technological innovation to drive the transformation and upgrading of their export structures.

(2) The Impact of Digital Trade on Industrial Competitiveness

The improvement of industrial competitiveness typically relies on enhanced production efficiency, innovation capacity, and market access, and digital trade has driven changes in the global competitiveness landscape through these aspects. First, digital technologies enhance the efficiency of information flow, capital flow, and logistics, helping businesses increase their competitiveness in global markets. Khan et al. (2023) noted that digitalized companies, through technologies such as big data analytics and artificial intelligence, not only optimize production processes and reduce costs but also respond to market demands in real time, thereby gaining a competitive edge in global markets [48]. For the manufacturing industry, digital technologies enable companies to quickly adjust production lines in response to changes in international markets, thereby enhancing their international competitiveness. Second, digital trade has reshaped the structure of global industrial chains and competition. Digitalization has fragmented the production process, and businesses no longer rely on traditional geographic advantages; instead, they choose the optimal produc-

tion bases through a combination of global digital platforms and logistics systems [49]. This global distributed production model means that industrial competitiveness is no longer solely dependent on traditional resource endowments but on companies' digital transformation and innovation capabilities. Digital production technology heralds the future of industrial development. Using digital tools to coordinate the value chain will significantly improve product quality, process efficiency, and international competitiveness [50]. Additionally, while promoting industrial upgrading, digital trade has facilitated the participation of small and medium-sized enterprises (SMEs), narrowing the competitive gap between large and small firms [51]. Digital platforms provide SMEs with opportunities to compete with large multinational corporations, allowing them to enter international markets using cost-effective digital tools and services, thereby enhancing the overall competitiveness of the industry.

In summary, there have been many studies on digital trade and the international competitiveness of the manufacturing industry at home and abroad. In the existing discussions, the importance of digital infrastructure, digital technologies themselves, digital platforms, digital ecosystems, enterprise capabilities, and resources [52,53] for the digital transformation of manufacturing enterprises through digital innovation cannot be ignored [54,55]. However, further research is needed on how digital trade can leverage its advantages to improve the productivity of manufacturing enterprises and enhance their international competitiveness. In this regard, this paper intends to draw on and incorporate relevant research results at home and abroad; analyze the direct and indirect impacts of digital trade on the development of the manufacturing industry based on the characteristic elements of digital trade; and propose research hypotheses. It will also analyze in depth the impact of digital trade on the international competitiveness of the manufacturing industry from both theoretical and empirical perspectives, based on the level of development of digital trade and the international competitiveness of the manufacturing industry. The results of the empirical analysis will then be used to propose ways to improve the international competitiveness of the manufacturing industry.

3. Theoretical Analysis of the Impact of Digital Trade on the International Competitiveness of the Manufacturing Industry

3.1. *The Direct Impact of Digital Trade on the International Competitiveness of the Manufacturing Industry*

3.1.1. Model Specification

According to Porter's (1990) theory of competitiveness, the core of international competitiveness lies in a country's or region's productivity level, especially how optimizing production factors and enhancing innovation improve overall economic efficiency [23]. Krugman (1994) further proposed that international competitiveness is crucially dependent on improving productivity, reducing costs, and fostering innovation and technological advancement to enhance overall economic productivity and competitiveness [56]. However, due to the multidimensional and complex nature of international competitiveness, comprehensively describing its variations using a single mathematical model is challenging in practical research. Based on Krugman's (1994) theory, Melitz (2003) [14] introduced the theory of heterogeneous firm trade, considering factors such as firm productivity and exploring the impact of productivity differences within the same industry on decisions related to market exit, export, and foreign direct investment (FDI). The research revealed that firms with lower productivity can only serve domestic markets, while those with higher productivity can expand into international markets through exports, indicating that productivity is one of the core factors determining industry competitiveness [14]. Therefore, the heterogeneous trade theory model effectively analyzes the productivity differences

between countries and firms, providing a powerful tool for understanding and predicting changes in international competitiveness.

The China Academy of Communications defines digital trade as a form where digital technologies play a key role in trade, with the most significant difference from traditional trade being the digitization of both trading methods and traded objects. Digital factors, such as digital technology, digital infrastructure, data, and talent, constitute the foundational resources and production factors driving the development of digital trade. The impact of digital trade on international competitiveness is primarily realized through the input and optimization of digital factors. Continuous investment in digital factors can directly affect the international competitiveness of manufacturing by improving production efficiency, reducing costs, and driving technological innovation.

First, the widespread application of digital technologies has significantly improved production efficiency, particularly in intelligent manufacturing and automated production processes, where enterprises can achieve higher precision and lower labor costs. Through technologies such as big data analysis and cloud computing, firms can optimize production processes in real time, reduce resource waste, and further lower production costs while enhancing efficiency. Second, the ongoing development of digital infrastructure provides enterprises with more efficient platforms, enabling the effective allocation of global factors, data, and resources; reducing search and transaction costs; and improving production efficiency and technological capabilities, thereby strengthening the international competitiveness of manufacturing. Furthermore, data, as a crucial production factor, not only drive the modernization of traditional industries but also generate a productivity multiplier effect driven by big data. Through big data analysis, manufacturing firms can precisely identify production bottlenecks and market demand, optimize production processes, reduce costs, and improve efficiency [57]. Additionally, digital factors promote technological innovation, offering firms a broader space for innovation. Through technological upgrades and new product development, companies can continuously improve their technological capabilities and market adaptability, thus enhancing their competitive advantage in international markets.

In conclusion, the input of digital factors not only plays a role in reducing costs but also enhances innovation, improving the productivity of manufacturing enterprises and thereby strengthening their international competitiveness.

Based on this, this paper draws on the heterogeneous trade theory models from Melitz (2003) [14] and Fan et al. (2020) [58], incorporating digital factor input into the production function of manufacturing enterprises. The modified model is used to analyze the impact mechanism of digital trade on the international competitiveness of manufacturing.

The model specification is outlined as follows:

(1) Consumer Behavior

In the context of an international trade model under monopolistic competition, it is assumed that the utility function of a typical consumer in the export destination country j takes the following form:

$$U_j = \int_{\omega \in \Omega_j} \ln[\lambda_{ij}(\omega)x_{ij}(\omega) + \bar{x}]d\omega \quad (1)$$

In this model, the subscript i represents firms from the export source country, and ω denotes the product that firm i exports to destination country j . The products produced by different firms are differentiated, with product quality denoted by $\lambda_{ij}(\omega)$. The subscript j represents the export destination country, which has a consumer group denoted by L_j , and the set of products available for consumption by these consumers is denoted by Ω_j ; $x_{ij}(\omega)$ represents the consumption quantity of product ω by consumers in country j . Specifically, $\bar{x}$ is a positive constant that reflects the initial consumption of non-imported products

by consumers in country j . Given the budget constraint, solving for utility maximization yields the demand function for product ω by consumers in the destination country:

$$x_{ij}(\omega) = L_j \left[\frac{E_j + \bar{x}P_j}{N_j + p_{ij}(\omega)} - \frac{\bar{x}}{\lambda_{ij}(\omega)} \right] \quad (2)$$

In this model, $p_{ij}(\omega)$ represents the price of product ω exported by firm i to destination country j . E_j denotes the total budget expenditure of consumers in country j on all products. N_j represents the total number of product varieties available for consumption in country j . P_j is the aggregate price index of all imported products in country j , given by the following:

$$P_j = \int_{\omega \in \Omega_j} \left(\frac{p_{ij}(\omega)}{\lambda_{ij}(\omega)} \right) d\omega \quad (3)$$

This study assumes that $\bar{x}$, L_j , E_j , N_j , and P_j are given exogenously.

(2) Producer Behavior

Given the demand function in Equation (2), the profit function for firm i exporting product ω to destination country j is expressed as follows:

$$\pi_{ij}(\omega) = L_j [p_{ij}(\omega) - c_{ij}(\omega)] \left[\frac{E_j + \bar{x}P_j}{N_j + p_{ij}(\omega)} - \frac{\bar{x}}{\lambda_{ij}(\omega)} \right] \quad (4)$$

where $c_{ij}(\omega)$ represents the marginal cost of firm i in producing product ω . Firms set prices to maximize their profits. By differentiating Equation (4) with respect to $p_{ij}(\omega)$ and solving the first-order condition for profit maximization, we obtain the following:

$$p_{ij}(\omega) = B_j \sqrt{c_{ij}(\omega) \lambda_{ij}(\omega)} \quad (5)$$

where $B_j = \sqrt{\frac{E_j + \bar{x}P_j}{N_j \bar{x}}}$ is a constant. For simplification, we assume $\bar{x} = 1$. Substituting Equation (5) into Equation (4) yields the following equation:

$$\pi_{ij}(\omega) = L_j \left[B_j - \sqrt{\frac{c_{ij}(\omega)}{\lambda_{ij}(\omega)}} \right]^2 \quad (6)$$

Equation (6) shows that a firm's profit depends solely on the ratio of marginal cost to product quality. Following Feenstra et al. (2014) [59], we define the ratio of marginal cost to product quality as the "quality-adjusted cost". Consequently, the firm's profit maximization problem is equivalent to minimizing the quality-adjusted marginal cost.

(3) Digital Factor Inputs and Production Technology

In a monopolistic competition market, we assume that firm i uses the following production technology to produce one unit of product ω with quality $\lambda_{ij}(\omega)$ (for simplicity, the subscripts for the firm and destination country are omitted below):

$$\lambda(\phi, \alpha, \beta) = \left[\phi \left(\frac{\beta D}{\alpha} \right)^\alpha \left(\frac{X}{1 - \alpha} \right)^{1 - \alpha} \right]^{\frac{1}{\phi}} \quad (7)$$

where D represents the digital factor input required for production, and X represents other production factors, such as labor, capital, and non-digital intermediate goods. α denotes the share or intensity of digital factor input in the firm's production, where $\alpha \in (0, 1)$. This reflects the level of digitalization in the firm's production; the higher the value of α , the greater the level of digitalization. This study primarily focuses on multi-product firms. Following Mayer et al. (2014) [60], ϕ represents the firm's productivity, with the distribution function $G(\phi)$, where the interval is $(\phi_{min}, +\infty)$. $\phi > 1$ measures the degree of product quality differentiation, with larger values of ϕ indicating smaller degrees of

differentiation. β represents the innovation efficiency of digital factor D ($\beta > 1$); the larger the value of β , the more innovation benefits can be derived from each unit of digital input.

First, from the firm's production process perspective, digital factor inputs help unlock the value of data, integrating automated production and information management and enabling the intelligent management of the entire product lifecycle based on data platforms. The firm can also quickly access relevant information on production, operations, and market conditions, enhancing internal control, improving decision-making efficiency, and reducing operational risks, thus improving innovation efficiency and productivity [61]. Second, digital factor inputs increase the likelihood of successful innovation, thereby fostering innovation within the firm [62], which in turn boosts the firm's productivity. Therefore, considering the innovation effect of digital factor inputs on the enhancement of productivity in Equation (7), the firm's final productivity is $\Phi = \phi\beta^\alpha$, where β^α represents the efficiency improvement of the firm's digital transformation.

Assume that in the factor market, firms are price takers for the factors of production, with the price levels for digital factors and non-digital factors being p_D and p_X , respectively. For the firm's digital factor input D , it can be further subdivided into domestic digital factor input D_d and foreign digital factor input D_f . Due to the presence of digital trade barriers, when firms import foreign digital intermediates, they must pay an additional markup. Therefore, the actual price of foreign-sourced digital intermediates consists of the production cost p_D and the digital trade barrier τ , i.e., τp_D . The actual price that the firm pays for digital factor inputs is $(D_d + \tau D_f)p_D/D$. Let $\tau = (D_d + \tau D_f)/D$. For the firm to undergo digital transformation, the following participation constraint must be satisfied:

$$\beta > \frac{p_D \tau}{p_X} = \beta_0 \quad (8)$$

where $\frac{p_D \tau}{p_X}$ represents the price distortion between digital and non-digital factors, and β_0 is the critical efficiency threshold for the use of digital factors. The implication of this equation is that the efficiency of digital factor input must be greater than the price distortion of the factors. Otherwise, the cost of digital transformation would be too high, and the firm would never recover its costs due to an unfavorable input–output ratio. Assuming the firm meets this condition, under the given product quality $\lambda(\phi, \alpha, \beta)$, the firm's input minimization for the production process can be solved, yielding the firm's marginal production cost c_P , as follows:

$$c_P(\phi, \alpha, \beta) = \frac{p_D^\alpha \tau^\alpha p_X^{1-\alpha} \lambda(\phi, \alpha, \beta)^\varphi}{\phi \beta^\alpha} \quad (9)$$

Additionally, when firms export products abroad, they must pay an iceberg-type variable cost γ per unit, where $\gamma > 1$, representing transportation, distribution, or other associated costs. Therefore, the firm's marginal cost c can be written as the sum of the marginal production cost and the iceberg cost, i.e., $c = c_P + \gamma$. Consequently, the quality-adjusted marginal cost is given by the following:

$$\frac{c}{\lambda}(\phi, \alpha, \beta) = \frac{p_D^\alpha \tau^\alpha p_X^{1-\alpha} \lambda(\phi, \alpha, \beta)^{\varphi-1}}{\phi \beta^\alpha} + \frac{\gamma}{\lambda} \quad (10)$$

As noted above, profit maximization requires firms to select the optimal product quality to minimize the quality-adjusted marginal cost. Thus, by differentiating the right-hand side of Equation (10) with respect to product quality λ and applying the first-order condition, the optimal product quality is derived as follows:

$$\lambda(\phi, \alpha, \beta) = \left(\frac{\gamma \phi \beta^\alpha}{(\varphi - 1) p_D^\alpha \tau^\alpha p_X^{1-\alpha}} \right)^{\frac{1}{\varphi}} \quad (11)$$

Substituting Equation (11) into Equations (5) and (9) yields the firm's optimal pricing and marginal cost as follows:

$$c(\phi, \alpha, \beta) = \frac{\phi}{\phi - 1} \gamma \quad (12)$$

$$p(\phi, \alpha, \beta) = B \sqrt[\frac{1}{\phi}]{\phi \left(\frac{\gamma}{\phi - 1} \right)^{\frac{1}{\phi} + 1} \left(\frac{\phi \beta^\alpha}{p_D^\alpha \tau^\alpha p_X^{1-\alpha}} \right)^{\frac{1}{\phi}}} \quad (13)$$

By solving Equations (12) and (13) simultaneously, the firm's market competitiveness at equilibrium can be derived:

$$Markup(\phi, \alpha, \beta) = \frac{p}{c} = B \sqrt[\frac{1}{\phi}]{\phi^{-1} \left(\frac{\phi - 1}{\gamma} \right)^{1 - \frac{1}{\phi}} \left(\frac{\phi \beta^\alpha}{p_D^\alpha \tau^\alpha p_X^{1-\alpha}} \right)^{\frac{1}{\phi}}} \quad (14)$$

(4) Analysis of Balanced Results

To examine the impact of digital factor input on international competitiveness, the logarithmic derivative of α with respect to both sides of Equation (14) is taken, resulting in the following:

$$\frac{\partial \ln Markup}{\partial \alpha} = \frac{1}{2\phi} \ln \left(\frac{\beta p_X}{p_D \tau} \right) > 0 \quad (15)$$

The above equation indicates that digital factor input has a positive effect on enhancing international competitiveness.

Based on Equations (11)–(14), we can derive the following:

$$\frac{\partial Markup}{\partial (c/\lambda)} = -\frac{B}{2} \left[\phi \left(\frac{\phi - 1}{\gamma} \right)^{\frac{1}{\phi} - 1} \left(\frac{\phi \beta^\alpha}{p_D^\alpha \tau^\alpha p_X^{1-\alpha}} \right)^{-\frac{1}{\phi} - \frac{3}{2}} \right] < 0, \quad \frac{\partial \ln(c/\lambda)}{\partial \alpha} = -\frac{1}{\phi} \ln \left(\frac{\beta p_X}{p_D \tau} \right) < 0 \quad (16)$$

Equation (16) indicates that digital trade influences the international competitiveness of manufacturing by impacting the marginal cost of quality adjustments. As the level of digitalization increases, the marginal cost of quality adjustments for manufacturing enterprises gradually decreases, thereby enhancing their international competitiveness. The key to this process is the widespread application of digital technologies, particularly big data and artificial intelligence. Existing research shows that digitalization can significantly improve a firm's ability to acquire market information quickly, absorb advanced technologies, and effectively utilize digital services. This, in turn, stimulates the firm's innovative momentum, enhances its research and development capabilities, and promotes rapid product iteration and quality improvement [63]. By accelerating product upgrades and improving quality, firms can enhance their competitiveness in the global market.

Furthermore, digital trade can improve production efficiency by lowering the marginal cost of quality products, thus enhancing international competitiveness. The reduction in production costs stems from two aspects: on one hand, digitalization improves a firm's production coordination and operational management efficiency; on the other hand, firms can lower production costs by optimizing resource allocation and procurement management. It is worth noting that, although in the theoretical model, the iceberg cost of a firm's export trade is considered fixed, numerous empirical studies have shown that digital trade can significantly reduce the iceberg costs associated with export sales [64]. This is mainly because digital trade alleviates information asymmetry in the market, reducing information search costs, matching costs, and communication costs, which enhances transaction efficiency, shortens the transaction process, and effectively reduces overseas agency and distribution costs through the establishment of digital platforms.

3.1.2. Mechanism Analysis

As fundamental resources and production factors driving the development of digital trade, digital elements directly influence the international competitiveness of manufacturing enterprises by improving production efficiency, reducing costs, and driving technological innovation.

First, the introduction of digital technologies has significantly enhanced the production efficiency of firms, especially in automated, intelligent, and precise production processes. Technologies such as cloud computing, big data, the Internet of Things, and artificial intelligence effectively optimize production processes, reduce resource waste, improve product quality, and thereby increase productivity. This improvement not only strengthens a firm's international competitiveness but also helps it capture a larger share of the global market. Additionally, with the continuous proliferation of digital technologies, firms can more precisely adjust production processes and allocate resources more efficiently, resulting in sustained growth in production efficiency. This aligns with the previously discussed equilibrium result, where digital technologies, by lowering the marginal cost of quality adjustments and enhancing production efficiency, further strengthen a firm's competitive advantage in the global market.

Second, the introduction of digital trade platforms, electronic payment systems, and information-sharing platforms has greatly improved the efficiency of cross-border trade, reducing intermediary fees, logistics costs, and time costs. Through digital methods, firms can reduce physical storage and transportation costs and further lower overall transaction costs by optimizing supply chain management and increasing transparency. Moreover, the application of digital platforms enables firms to directly connect with upstream and downstream supply chain partners and reduce intermediary links, thereby enhancing the efficiency and flexibility of the supply chain. This process significantly lowers the marginal costs in production and quality adjustments, enabling firms to enter international markets at more competitive prices, thus further increasing market share.

Third, enhanced technological innovation is a key driver of productivity improvement and cost reduction. The widespread application of digital technologies, particularly in fields like artificial intelligence, big data, and cloud computing, provides firms with more opportunities for innovation. By adopting these advanced technologies, firms can optimize production processes, improve product quality, and significantly enhance production efficiency through intelligent manufacturing and automated production lines while also reducing labor costs and error rates. These innovative technologies not only boost productivity but also effectively reduce resource waste, further lowering production costs. However, the effective application of digital technologies depends not only on the technologies themselves but also on the availability of high-quality talent to drive them. By cultivating and attracting skilled technical talent, firms can accelerate product development, optimize production processes, improve technical capabilities, and enhance innovation, thereby increasing their international competitiveness. Therefore, the combination of technological innovation and talent directly drives firms to achieve a technological leadership position and competitive advantage in the global market.

Finally, in terms of driving industrial transformation and upgrading, on the one hand, digital technologies, through automation and intelligent production systems, have optimized traditional production processes, enabling firms to increase production efficiency, reduce resource waste, and improve product quality. This process not only enhances firms' immediate competitiveness but also lays the foundation for long-term development. On the other hand, digital trade provides platform support for the development of emerging industries, especially the rise of smart manufacturing and digital service industries. Through digital platforms, these emerging industries can accelerate technological innova-

tion and redefine market models, driving overall technological progress in manufacturing. Moreover, digital trade allows traditional manufacturing industries to more flexibly adapt to changing global market demands. By adopting refined management practices and expanding international markets through cross-border e-commerce platforms, firms not only enhance their market responsiveness but also strengthen their adaptability to global markets. Therefore, digital trade drives the comprehensive transformation and upgrading of manufacturing industries, enabling firms to effectively improve production efficiency and product quality in the short term while continuously fueling long-term innovation, thereby enhancing their competitiveness in international markets.

In summary, digital trade, through the flow of digital technologies, digital infrastructure, data, and talent, directly affects key variables such as productivity, cost, and innovation capacity, thereby enhancing a firm's competitiveness in the global market. Based on this analysis, the following hypothesis is proposed:

Hypothesis 1. *Digital trade contributes to the enhancement of the international competitiveness of manufacturing industries.*

3.2. The Impact Mechanism of Digital Trade on the International Competitiveness of the Manufacturing Industry

3.2.1. Capital-Driven Effect

The rapid development of digital trade has crested new opportunities for the manufacturing industry, with foreign direct investment (FDI) playing a pivotal role. Foreign capital not only enhances the production capacity of domestic enterprises through capital inflows but also promotes the digital transformation and industrial upgrading of the manufacturing industry through technology introduction, supply chain collaboration, and talent acquisition.

(1) Technology Spillover Effect

Technology spillover is one of the most significant effects associated with foreign direct investment (FDI). The endogenous growth theory emphasizes that technological progress is the core driver of economic growth, and technology spillovers are a key mechanism for advancing industrial progress. Foreign capital not only provides direct financial support but also introduces advanced technologies, management practices, and innovative models, creating valuable opportunities for domestic enterprises to enhance their competitiveness. Foreign-invested enterprises bring these innovations into the domestic market through direct investments, collaborations, and mergers and acquisitions. In this process, domestic enterprises benefit from technological upgrades and improvements in management practices through knowledge sharing and spillover effects [65]. Specifically, when foreign-invested enterprises establish local production bases, they introduce advanced production technologies, driving innovations in management techniques, market strategies, and production processes. The flow of these technologies, management practices, and market knowledge fosters technological advancement and innovation across the industry and region. The technology spillover effect is not limited to direct collaborations between foreign-invested and domestic enterprises; it also extends to surrounding suppliers and related businesses, forming a broader industrial cluster that enhances regional competitiveness. For example, local production bases of foreign-invested enterprises typically drive improvements in technological standards, encouraging local suppliers to adopt more efficient production technologies and raising standards in areas such as raw material processing, product design, and quality management. As technological progress spreads throughout the upstream and downstream sectors of the industrial chain, this spillover effect gradually extends across the entire regional industrial chain, fostering high-quality

economic development. Moreover, the technology spillover effect encourages domestic enterprises to continually innovate, boosting productivity and enhancing the overall innovation capacity and production efficiency of the region. Thus, the technology spillover effect from foreign investment not only promotes the direct growth of domestic enterprises but also drives industrial clustering and contributes to the sustainable development of regional economies.

(2) The Shift in Cross-Border Investment Motives

The rise of digital trade has significantly transformed the investment motives of foreign-invested enterprises. Traditionally, foreign direct investment (FDI) was primarily driven by resource acquisition and market expansion. However, the advent of digital trade has shifted these motives [66]. According to the transaction cost theory, digitalization has reduced information search, marketing, and transaction costs, thereby enhancing the efficiency of cross-border investments. As a result, investment motives have increasingly shifted from traditional resource- and market-driven factors toward industry digitalization and innovation.

On the one hand, digitalization has driven the transformation of cross-border investment motives, particularly in the manufacturing industry. Multinational corporations now focus not only on cost and market size but increasingly on the potential for digital transformation within enterprises. For instance, manufacturing enterprises with digital capabilities such as intelligent production and flexible management have become new targets for multinational investment. Through these investments, multinational corporations can not only enhance their technological capabilities but also gain a competitive edge in the global market while driving the optimization of industrial chains.

On the other hand, digitalization has increased the efficiency of managing cross-border investments. Enterprises no longer need to establish large-scale localized management systems in each market but can reduce management costs and complexity through remote management, digital platforms, and global resource allocation. For example, multinational corporations can use cloud platforms to monitor the operations of their global subsidiaries in real time, enabling them to adjust production and sales strategies promptly and further reduce risks associated with cross-border investments.

In summary, the rise of digital trade has fundamentally changed cross-border investment motives. Investment decisions by foreign-invested enterprises are no longer confined to resource acquisition and market expansion but are increasingly centered on digital transformation and technological innovation. This shift has not only enhanced the efficiency of cross-border investments but also driven the upgrading of global industrial chains and the technological advancement of domestic enterprises.

(3) The Introduction of Digital Talent and Innovation-Driven Growth

According to the human capital theory, technological progress and industrial development rely on the accumulation of knowledge and skills. The quality and quantity of talent are particularly critical in innovation-driven sectors, directly determining industry competitiveness. The rise of digital trade has accelerated the global movement of high-skilled talent, especially professionals with digital skills, technical expertise, and management experience. Through foreign direct investment (FDI), the manufacturing industry not only gains financial support but also attracts talent with advanced technological and managerial expertise. The introduction of these skilled individuals provides essential knowledge for technological innovation within manufacturing enterprises. Their efficient management models and innovative thinking further enhance the global competitiveness of these companies [67]. At the same time, the innovation-driven growth theory posits that innovation is the core driver of economic growth, and the foundation of innovation lies in high-quality human capital. Foreign-invested enterprises not only directly improve the

technical and managerial capabilities of domestic companies but also bring new, innovative concepts and methods, driving the digital transformation of domestic enterprises in areas such as product development, production processes, and market expansion. This transformation not only strengthens the global competitiveness of domestic enterprises but also promotes the upgrading of industrial structures, helping companies better respond to rapidly changing market demands and technological challenges. Moreover, the presence of foreign-invested enterprises in local markets actively promotes the development of human capital in domestic enterprises. Through collaboration between multinational corporations and local companies, domestic enterprises are able to enhance their human resources through technical training, knowledge exchange, and talent mobility. These collaborations not only help domestic enterprises improve their management and technical capabilities but also strengthen their innovation capacity, further driving their sustainable development. Thus, foreign-invested enterprises, by driving the introduction of high-quality talent and deepening cross-border cooperation, promote the improvement of human capital and technological innovation in domestic companies, providing solid support for enhancing the global competitiveness of these companies.

(4) Supply Chain Collaboration and the Industrial Cluster Effect

In the context of digital trade, foreign-invested enterprises have not only driven local technological advancements through capital injection but also significantly enhanced the production efficiency and market competitiveness of domestic companies through global supply chain collaboration. The supply chain management theory posits that optimizing global supply chains improves resource allocation efficiency and fosters closer cooperation among upstream and downstream enterprises. As digitalization advances, the sharing of knowledge, technology, and experience within the supply chain has become crucial to improving corporate production efficiency and innovation capacity.

By establishing global supply chain networks, foreign-invested enterprises introduce advanced production technologies, management expertise, and innovative ideas, driving technological progress in domestic industries. The application of digital technologies, such as cloud computing, big data analytics, and the Internet of Things, has further enabled real-time information transmission, increasing the efficiency of supply chain operations. These technologies help foreign-invested enterprises optimize production planning, inventory management, and demand forecasting, which reduces waste, improves resource allocation, and boosts production efficiency. This digital supply chain model not only enhances the production efficiency of foreign-invested enterprises but also strengthens the technological, managerial, and operational capabilities of domestic enterprises.

Moreover, the collaboration between foreign-invested enterprises and domestic companies has further enhanced the industrial cluster effect. According to the regional economic clustering theory, synergies among enterprises within industrial clusters contribute to technological innovation, productivity enhancement, and global market competitiveness. In the digital age, foreign-invested enterprises not only provide capital and technological support but also help domestic enterprises share global market resources by establishing close industry chain relationships, thereby enhancing their competitiveness. The interaction between foreign-invested and domestic enterprises within global supply chains has driven the collaborative development of various supply chain links, accelerating the digital transformation of domestic enterprises and improving the overall innovation capability and production efficiency of the industry.

This supply chain collaboration and industrial cluster effect have not only strengthened the market competitiveness of domestic enterprises but also optimized global resource allocation. Through their global supply chain networks, foreign-invested enterprises help domestic companies enhance their production capacity and market responsiveness, thus

improving the efficiency and competitiveness of the entire industrial chain. Therefore, the supply chain collaboration and industrial cluster effects brought about by digitalization have driven the modernization transformation of domestic industries and facilitated the rapid rise of domestic enterprises in the global market.

Hypothesis 2. *Digital trade enhances the international competitiveness of manufacturing by attracting foreign investment.*

3.2.2. The Driving Effect of Digital Technology

With the rapid development of digital technology and the rise of digital trade, the competitiveness of the manufacturing industry is no longer solely dependent on traditional production capabilities and cost advantages. Instead, it places greater emphasis on technological innovation, the enhancement of research and development (R&D) capabilities, and the optimization of production efficiency. The application of digital technology has not only accelerated production processes but also significantly enhanced the international competitiveness of manufacturing through its profound impact on R&D, production efficiency, supply chain optimization, and market competition. The following analysis will explore how digital technology boosts the international competitiveness of the manufacturing industry by examining its roles in R&D, production efficiency, supply chains, and sales, supported by relevant theoretical frameworks.

(1) The Driving Role of Digital Technology in R&D

Digital technology accelerates the diffusion of technological innovations, drives the flow of technologies across borders, and subsequently enhances the R&D capabilities and innovation levels of manufacturing enterprises. The absorptive capacity theory reveals a critical capability of enterprises in technological innovation: the ability to absorb and transform external knowledge [68]. Driven by digital trade, manufacturing companies are able to rapidly access technological advancements on a global scale, which, in turn, accelerates R&D activities and improves efficiency. For example, through global digital platforms, manufacturing firms not only gain access to the latest product designs, smart manufacturing technologies, and automation equipment but also leverage digital tools such as the Internet and cloud computing to quickly incorporate these advanced technologies into their local production and R&D systems. As external technologies are introduced and knowledge is absorbed, enterprises can not only enhance their R&D capabilities but also localize and adapt existing technologies, further driving independent innovation and technological breakthroughs.

Furthermore, the innovation diffusion theory also provides theoretical support for this process. This theory posits that the diffusion of technology is an accelerating process, particularly in a digital context, where the efficiency of technology and knowledge dissemination is greatly enhanced [69]. With the promotion of digital trade, global innovation outcomes and technological advancements can spread across regions and enterprises in a much shorter time frame. This efficient diffusion of technology not only facilitates the absorption of new technologies by enterprises but also accelerates the promotion and application of technological innovations, raising the overall R&D level in the manufacturing industry. Moreover, under traditional R&D models, resource allocation is often constrained by time, space, and information asymmetry. However, digital technologies make resource allocation more efficient. Through big data and cloud computing, enterprises can access a wide range of information necessary for R&D in real time, including market demand, technological trends, and competitive dynamics, thereby providing data-driven support for R&D decision-making.

(2) The Role of Digital Technology in Improving Production Efficiency

In terms of improving production efficiency, digital technology has significantly boosted the productivity of the manufacturing industry by optimizing the allocation of production factors and enabling the intelligent management of production processes. According to the theory of production function, the efficient allocation of production factors is key to improving productivity. Digital technologies, such as big data analytics, artificial intelligence, and automation, provide enterprises with effective tools to optimize production processes. Through digital systems, businesses are able to monitor production progress in real time and precisely schedule resources such as equipment, personnel, and raw materials, thereby reducing time waste and resource idle time in production, which enhances overall efficiency [70]. Moreover, the theory of human-machine compatibility also provides theoretical support for the improvement of production efficiency. This theory suggests that the application of digital technologies not only replaces some traditional manual labor but also collaborates with human resources in certain areas, thereby improving production efficiency. The integration of artificial intelligence and automated equipment enables enterprises to complete more complex production tasks in a shorter time. This synergistic effect allows manufacturing enterprises to enhance production efficiency while simultaneously improving the work efficiency of their research and development departments. Furthermore, digital technology plays a crucial role in lean manufacturing. By continuously monitoring production data, companies can identify bottlenecks and inefficiencies in the production process and take timely measures for adjustment. The implementation of lean production not only improves production efficiency and reduces costs but also provides more resources for research, development, and market innovation.

(3) The Role of Digital Technology in Supply Chain Optimization

The role of digital technology in supply chain optimization mainly lies in enhancing the efficiency of information flow and improving collaboration across various stages of the supply chain. According to the supply chain coordination theory, efficient operation across supply chain stages can be achieved through information sharing and real-time coordination. The widespread application of digital technologies, particularly cloud computing and the Internet of Things, has eliminated the information delays and coordination inefficiencies inherent in traditional supply chain management, enabling all parties in the supply chain to share real-time data through digital platforms. This facilitates a more accurate response to market demand and production plans. A digital supply chain can track products in real time from raw material procurement through production and also predict market demand and production progress, enabling companies to prepare production in advance. With the aid of digital technologies, suppliers, manufacturers, and distributors can quickly adjust production plans while avoiding resource waste and production bottlenecks, thereby enhancing overall supply chain efficiency and responsiveness. Furthermore, digital technologies enable manufacturing enterprises to achieve precise inventory management, thereby reducing inventory accumulation and overproduction. This not only optimizes resource utilization but also improves the operational efficiency of the supply chain by lowering inventory costs. Moreover, digital supply chains promote seamless collaboration between global suppliers and distributors. Shen G. et al. (2020) highlighted that digital technology facilitates the smooth flow of knowledge and data both within enterprises and across upstream and downstream industries [71]. Through digital platforms, manufacturing enterprises can collaborate more efficiently with global suppliers, flexibly adjust production resources and distribution plans, and respond to the rapidly changing global market demand. This synergy in multinational supply chains enables manufacturing industries to adapt more flexibly to global market changes, thereby strengthening their competitive responsiveness.

(4) The Role of Digital Technology in Enhancing Market Competitiveness

The role of digital technology in enhancing market competitiveness is primarily reflected in optimizing market feedback mechanisms and enhancing a company's ability to quickly respond to market changes. According to the market matching theory, timely feedback and the precise matching of information are key to improving market efficiency. In the digital age, the manufacturing industry can capture changes in market demand in real time through technologies such as big data analytics, social media monitoring, and consumer behavior tracking, enabling swift adjustments to product development directions and production plans. Digital technologies enable manufacturing enterprises to obtain more precise market demand data, allowing them to fully consider consumer-specific needs during the research and development stage. This market-driven R&D model not only enables manufacturing products to quickly respond to market changes but also allows for customization based on personalized consumer demands, enhancing both market adaptability and product competitiveness.

Moreover, the increased use of digital technology enables companies to accurately predict market trends and adjust product strategies based on instantaneous feedback, ensuring they remain at the forefront of both technology and market developments. In this process, digital trade has driven deeper integration and information sharing across global markets. Through digital platforms, manufacturing enterprises can establish closer connections with global consumers and partners, fostering technological innovation and product optimization. This global network not only enables companies to better track global technological trends and market demands but also overcomes geographical limitations, helping businesses expand into broader market spaces. The widespread use of digital technology further extends the high-end of the manufacturing value chain within the "smile curve" framework. Manufacturing is no longer solely reliant on low-end production stages but, driven by digital technology, strengthens high-value-added stages such as R&D, design, and brand development, thereby enhancing its competitive position in the global market [72].

Hypothesis 3. *Digital trade can enhance manufacturing's international competitiveness by improving technological R&D capabilities.*

3.2.3. Spatial Spillover Effect

The spatial spillover effect refers to the impact of economic activities, technological innovations, and other resource changes in a particular region or enterprise that not only affect the region or enterprise itself but also, through geographic or economic connections, influence the economic development, technological progress, and productivity of surrounding areas or other enterprises. The Marshallian externality theory, introduced by Alfred Marshall, is one of the most classic theoretical foundations for spatial spillover effects. This theory emphasizes the role of industrial agglomeration in promoting technological innovation and productivity improvement.

On the one hand, it leads to technological externalities and knowledge spillovers. According to Marshall's view, when an industry agglomerates in a specific region, it fosters technological exchange and knowledge sharing among firms. This agglomeration not only concentrates technological progress and innovation but also facilitates the rapid spillover of technological and innovative achievements to surrounding areas, driving technological progress and industrial upgrading in neighboring regions. Under the context of digital trade, this effect is further strengthened. Digital trade, through cross-border e-commerce, online platforms, cloud computing, and big data technologies, breaks traditional geographical and physical barriers, reducing the costs of information transmission and technological diffusion. As a result, technologies, management experience, and innovative results can

quickly spread from one region to another, thereby enhancing the depth and breadth of economic connections between previously unconnected regions [73]. Furthermore, as marginal costs of inter-sectoral linkages continue to decline, manufacturing enterprises benefit from an increasing marginal effect. This marginal effect promotes factor mobility, accelerates inter-regional exchanges and cooperation, and further strengthens the spatial spillover of knowledge and technology, driving economic growth in surrounding areas [74]. Specifically, in manufacturing, leading enterprises in one region can use digital means (such as cross-border e-commerce platforms, online collaboration tools, etc.) to transmit innovative technologies, production methods, and even management models to neighboring or multinational manufacturing enterprises. This can significantly enhance the production efficiency and product quality of enterprises in neighboring regions, thereby promoting technological upgrades and modernization processes in these areas. In addition, regions with rapid development of digital trade not only benefit from cross-regional resource integration and technology spillovers, enhancing the utilization of digital elements in surrounding areas and realizing regional coordination effects, but also facilitate the learning and adoption of advanced digital trade models by manufacturing enterprises in neighboring regions.

On the other hand, agglomeration effects occur. According to Marshallian externality theory, the geographical concentration of industries makes it easier for related enterprises and upstream and downstream sectors to share resources, information, and technologies, thereby improving the overall regional economic efficiency and industrial competitiveness. In the context of digital trade, the agglomeration effect has been expanded beyond physical distances. Digital platforms have created new possibilities for cross-regional and cross-national resource sharing and technological cooperation. With the widespread adoption of digital infrastructure (such as cloud computing services, data storage, etc.), manufacturing enterprises can more easily participate in global supply chains, access global market demand information, and share global technological and management resources. For example, leading regions in manufacturing can quickly provide enterprises in other regions with the latest product designs, process technologies, and management concepts through digital trade platforms. This digital agglomeration effect enables the technological spillover, originally confined to geographic agglomeration, to expand rapidly to broader regions, further enhancing the global competitiveness of manufacturing.

Hypothesis 4. *Digital trade generates spatial spillover effects that can enhance the international competitiveness of manufacturing in neighboring regions.*

4. Analysis of China's Digital Trade and Manufacturing Industry's International Competitiveness

4.1. Measurement of China's Digital Trade Development Level

Although China's digital trade has a large scale of exports and imports and rapid export growth, there are still significant regional differences in digital trade. In order to accurately and objectively measure the gap in the development level of digital trade among China's provinces, this paper, based on the connotation and characteristics of digital trade and existing research, follows the principles of comprehensiveness, availability, and comparability and refers to the approach of Ye (2024) [22] to construct an indicator system with five dimensions: digital trade foundation, digital technology environment, digital trade potential, digital trade capacity, and digital trade industry (see Table 1). The 31 provinces of China (excluding Hong Kong, Macao, and Taiwan) are used as the research object, and the period from 2012 to 2022 is selected as the research period. The entropy weight method is combined with the above evaluation indicators to comprehensively

evaluate the development level of digital trade in each province of China. The data are sourced from the China Statistical Yearbook (2013–2023) to ensure consistency and validity.

Table 1. Indicator system for evaluating the level of development of digital trade.

Level 1 Indicators	Level 2 Indicators	Level 2 Indicator Symbols
Digital trade foundation	Number of domain names (unit: 10,000)	X1
	Number of web pages (unit: 10,000)	X2
	Internet broadband access ports (unit: 10,000)	X3
	Mobile telephone exchange capacity (unit: 10,000 households)	X4
	Mobile phone base stations (unit: 10,000)	X5
	Length of long-distance fiber-optic cable (unit: kilometers)	X6
	Mobile internet access traffic (unit: 10,000 GB)	X7
Digital technology environment	Number of patent applications	X8
	Number of patents granted	X9
	R&D expenditure of industrial enterprises above the designated size (unit: RMB 10,000)	X10
	Number of people employed in information transmission, software, and information technology services (unit: RMB 10,000)	X11
	Gross regional product (unit: RMB 100 million)	X12
Digital trade potential	Proportion of science and technology expenditure within regional fiscal expenditure (%)	X13
	Regional import and export volume (unit: RMB 100 million)	X14
	E-commerce sales (unit: RMB 100 million)	X15
Digital trade capacity	Software business revenue (unit: RMB 10,000)	X16
	Total telecommunications business volume (unit: RMB 100 million)	X17
Digital trade industry	Number of listed companies in the digital trade industry	X18
	Fixed asset investment in the information transmission, software, and information technology services industry (unit: RMB 100 million)	X19

Source: compiled by the author.

4.1.1. Empowerment Based on the Entropy Weight Method

Drawing on the approach of Yao (2021) [75], the entropy weight method is used to measure the level of digital trade development in 31 provinces and cities in China. The entropy weight method is an objective weighting method that calculates the weight of an indicator based on the degree of variation in the indicator data of the evaluation object. This method uses the entropy value to determine the degree of dispersion of an indicator. The smaller the entropy value of an indicator, the greater its degree of dispersion (the more data, the more dispersed). Therefore, its weight, that is, its impact on the overall evaluation, is more significant, and vice versa. The reason for choosing this method is that the entropy weight method is an objective weighting method. Using it to determine the weight of evaluation indicators can avoid the shortcomings of traditional expert-based weighting methods, such as the FAHP method, which is susceptible to subjective adverse influences. The specific steps for determining weights based on the entropy weight method are as follows:

(1) Comparability of Indicators

A comprehensive evaluation is a statistical analysis process that involves aggregating and summarizing multiple complex indicators into a single composite indicator. Prior to aggregation and summarization, it is essential to perform standardized technical processing on each individual indicator to ensure comparability. The formula for the standardized calculation of indicator data is as follows:

$$\text{Positive indicators : } \lambda_{ij} = \frac{Y_{ij} - \min(Y_j)}{\max(Y_j) - \min(Y_j)} \quad (17)$$

$$\text{Negative indicators : } \lambda_{ij} = \frac{\max(Y_j) - Y_{ij}}{\max(Y_j) - \min(Y_j)} \quad (18)$$

In Equations (17) and (18), λ_{ij} is the indicator score of the j^{th} indicator of the i^{th} province, Y_{ij} is the original data of the j^{th} indicator of the i^{th} province in a particular year, $\max(Y_j)$ is the most considerable value in the current year's data of the j^{th} indicator of the 31 provinces, and $\min(Y_j)$ is the smallest value. For the positive indicator, the bigger, the better, and for the negative indicator, the smaller, the better.

Since the above indicators are positively related to the level of comprehensive digital trade development, we take the positive indicators in the construction of entropy weights, and the value of each type of indicator calculated by Formula (1) is λ_{ij} , forming the indicator matrix $(\lambda_{ij})_{n \times m}$, where n represents the number of sample provinces and m represents the number of evaluation indicators.

(2) Measuring objective weights W_j :

$$W_j = \frac{1 - E_j}{\sum_{j=1}^m 1 - E_j} \quad (19)$$

In Equation (19), E_j is the entropy value of the j^{th} indicator, where $E_j = \frac{-1}{\ln m} \sum_{i=1}^n P_{ij} \ln P_{ij}$; P_{ij} is the distribution of the weight of the j^{th} indicator among provinces, where $P_{ij} = \frac{\lambda_{ij}}{\sum_{i=1}^n \lambda_{ij}}$; and $\ln(0) = 0$ when P_{ij} is 0.

(3) Calculation of U_i for each province in different years:

$$U_i = \sum_{j=1}^m (w_j \times \lambda_{ij}), i \in (1, 2, \dots, n) \quad (20)$$

4.1.2. Comprehensive Evaluation Measurement

The above steps were used to calculate the weights of the indicators for developing digital trade in 31 provinces and cities, such as Beijing, from 2012 to 2022, as shown in Table 2. As can be seen from Table 2, X_2 has the most significant weight, accounting for more than 11%, followed by X_1 , X_8 , X_9 , X_{10} , X_{11} , X_{14} , X_{15} , X_{16} , and X_{18} , in that order, each accounting for more than 5%.

Table 2. Weighting of indicators for evaluating the development level of digital trade in China.

Indicators	Weights	Indicators	Weights	Indicators	Weights	Indicators	Weights	Indicators	Weights
X1	0.07	X5	0.03	X9	0.06	X13	0.03	X17	0.03
X2	0.11	X6	0.03	X10	0.06	X14	0.08	X18	0.10
X3	0.03	X7	0.03	X11	0.05	X15	0.06	X19	0.03
X4	0.02	X8	0.06	X12	0.03	X16	0.09		

Data source: calculated and compiled by the author.

The development level of digital trade in 31 provinces and cities in China from 2012 to 2022 is comprehensively calculated based on the above indicator weights, which are ranked according to their average index, as shown in Table 3. From 2012 to 2022, the development level of digital trade in all provinces in China showed an increasing trend, consistent with the overall development trend of digital trade in China. Among the analyzed regions, Guangdong, Jiangsu, and Beijing ranked among the top three in terms of the development level of digital trade. Jiangxi had the fastest increase, rising from 21st place in 2012 to 14th place in 2022, while Inner Mongolia and Liaoning experienced negative growth. Inner Mongolia fell from 13th place in 2015 to 23rd place in 2022, while Liaoning fell from 9th place in 2012 to 18th place in 2022 (see Table 4).

Table 3. Evaluation and ranking of the development level of digital trade in 31 provinces and cities in China from 2012 to 2022.

Region	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Average Index	Sequence
Guangdong	0.82	0.85	0.88	0.81	0.89	0.85	0.88	0.88	0.88	0.86	0.86	0.86	1
Jiangsu	0.59	0.62	0.62	0.56	0.59	0.55	0.55	0.55	0.56	0.54	0.54	0.57	2
Beijing	0.51	0.54	0.57	0.54	0.58	0.56	0.56	0.58	0.57	0.60	0.61	0.57	3
Zhejiang	0.50	0.46	0.47	0.45	0.49	0.45	0.45	0.46	0.46	0.44	0.45	0.46	4
Shandong	0.33	0.42	0.40	0.35	0.38	0.36	0.35	0.34	0.35	0.36	0.37	0.36	5
Shanghai	0.33	0.32	0.35	0.32	0.36	0.33	0.32	0.33	0.34	0.34	0.33	0.33	6
Sichuan	0.19	0.20	0.22	0.22	0.24	0.23	0.24	0.26	0.27	0.26	0.25	0.24	7
Fujian	0.21	0.19	0.20	0.22	0.26	0.28	0.27	0.25	0.23	0.23	0.23	0.23	8
Henan	0.17	0.17	0.19	0.19	0.21	0.21	0.22	0.22	0.25	0.24	0.23	0.21	9
Hubei	0.15	0.15	0.17	0.18	0.18	0.18	0.18	0.20	0.19	0.18	0.19	0.18	10
Anhui	0.13	0.14	0.15	0.15	0.18	0.17	0.18	0.18	0.20	0.20	0.20	0.17	11
Hebei	0.15	0.15	0.15	0.13	0.16	0.16	0.16	0.17	0.18	0.18	0.18	0.16	12
Hunan	0.14	0.13	0.14	0.14	0.15	0.15	0.16	0.18	0.18	0.17	0.18	0.16	13
Liaoning	0.18	0.19	0.19	0.17	0.15	0.13	0.12	0.12	0.12	0.11	0.11	0.15	14
Shaanxi	0.10	0.11	0.12	0.12	0.13	0.12	0.13	0.13	0.12	0.12	0.12	0.12	15
Tianjin	0.11	0.13	0.13	0.12	0.12	0.11	0.11	0.10	0.11	0.10	0.09	0.11	16
Jiangxi	0.08	0.07	0.09	0.09	0.10	0.11	0.11	0.12	0.13	0.13	0.12	0.10	17
Chongqing	0.08	0.08	0.10	0.10	0.11	0.10	0.10	0.10	0.11	0.11	0.11	0.10	18
Guangxi	0.08	0.08	0.12	0.08	0.09	0.10	0.10	0.11	0.12	0.11	0.11	0.10	19
Yunnan	0.08	0.09	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	20
Heilongjiang	0.09	0.11	0.10	0.08	0.09	0.08	0.08	0.07	0.07	0.07	0.07	0.08	21
Inner Mongolia	0.07	0.07	0.08	0.15	0.08	0.07	0.07	0.07	0.07	0.06	0.07	0.08	22
Guizhou	0.05	0.06	0.06	0.06	0.07	0.08	0.08	0.09	0.09	0.10	0.10	0.08	23
Shanxi	0.07	0.08	0.08	0.06	0.07	0.07	0.08	0.07	0.08	0.08	0.08	0.07	24
Jilin	0.06	0.06	0.07	0.06	0.08	0.08	0.07	0.06	0.07	0.05	0.06	0.06	25
Xinjiang	0.05	0.05	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	26
Gansu	0.04	0.04	0.04	0.04	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.04	27
Hainan	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03	28
Ningxia	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	29
Qinghai	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	30
Tibet	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	31

Data source: calculated and compiled by the author.

Table 4. Ranking and maximum sequence differences for evaluating the development level of digital trade in each province in China from 2012 to 2022.

Region	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Maximum Sequence Difference
Beijing	3	3	3	3	3	2	2	2	2	2	2	1
Tianjin	15	15	15	16	16	16	17	19	19	19	21	6
Hebei	12	12	12	15	12	12	13	13	13	12	13	3
Shanxi	23	21	21	24	25	25	23	23	22	22	22	4
Inner Mongolia	22	23	23	13	22	24	25	24	25	24	23	12
Liaoning	9	8	8	11	14	14	15	15	15	16	18	10
Jilin	24	24	24	23	23	23	24	25	24	26	26	3
Heilongjiang	17	16	16	22	21	21	22	22	23	23	24	8
Shanghai	6	6	6	6	6	6	6	6	6	6	6	0
Jiangsu	2	2	2	2	2	3	3	3	3	3	3	1
Zhejiang	4	4	4	4	4	4	4	4	4	4	4	0
Anhui	14	13	13	12	11	11	11	11	10	10	10	4
Fujian	7	9	9	8	7	7	7	8	9	9	9	2
Jiangxi	21	22	22	19	18	17	16	16	14	14	14	8
Shandong	5	5	5	5	5	5	5	5	5	5	5	0
Henan	10	10	10	9	9	9	9	9	8	8	8	2
Hubei	11	11	11	10	10	10	10	10	11	11	11	1
Hunan	13	14	14	14	13	13	12	12	12	13	12	2
Guangdong	1	1	1	1	1	1	1	1	1	1	1	0
Guangxi	19	19	19	21	19	19	18	17	17	17	17	4
Hainan	28	28	28	28	28	28	29	28	28	28	28	1
Chongqing	18	20	20	18	17	18	19	18	18	18	16	4
Sichuan	8	7	7	7	8	8	8	7	7	7	7	1
Guizhou	25	25	25	25	24	22	21	21	21	20	19	6
Yunnan	20	18	18	20	20	20	20	20	20	21	20	3
Tibet	31	31	31	31	31	31	31	31	30	31	31	1
Shaanxi	16	17	17	17	15	15	14	14	16	15	15	3
Gansu	27	27	27	27	27	27	27	27	27	27	27	0
Qinghai	29	29	29	29	29	30	30	30	31	30	30	2

Table 4. *Cont.*

Region	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Maximum Sequence Difference
Ningxia	30	30	30	30	30	29	28	29	29	29	29	2
Xinjiang	26	26	26	26	26	26	26	26	26	25	25	1

Data source: calculated and compiled by the author.

According to the range of variation in the maximum serial difference, there are three development types: stable development (fluctuation between 0 and 1), fluctuating development (fluctuation between 2 and 3), and jumping development (fluctuation greater than or equal to 4). From the perspective of the fluctuation of the maximum sequential difference in the development of digital trade in China's provinces (see Table 5), 12 provinces represent stable development types, 9 provinces represent fluctuating development types, and 10 provinces represent jump development types. The level of development of digital trade in China's provinces is relatively stable. The distribution of the regional development of digital trade is basically in sync with economic development. Areas with a high economic level also have a better development of digital trade, while areas with a relatively low economic level have a relatively lagging development of digital trade.

Table 5. Classification of changes in the ranking of China's level of digital trade development.

Categorization	Region
Stable development	Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Hubei, Guangdong, Hainan, Sichuan, Tibet, Gansu, Xinjiang
Fluctuating development	Hebei, Jilin, Fujian, Henan, Hunan, Yunnan, Shaanxi, Qinghai, Ningxia
Jumping development	Tianjin, Shanxi, Inner Mongolia, Liaoning, Heilongjiang, Anhui, Jiangxi, Guangxi, Chongqing, Guizhou

Data source: calculated and compiled by the author.

4.2. Analysis of the Current Situation of the International Competitiveness of China's Manufacturing Industry

4.2.1. Measurement of China's Manufacturing Industry's International Competitiveness

The overall quality level of China's manufacturing industry is steadily improving, and its industry and regional quality development capabilities continue to improve. However, insufficient innovation, limited technology, low informatization, and a loss of comparative advantage have resulted in excess low-end manufacturing capacity in China that cannot meet high-end demand. Therefore, we should address China's manufacturing industry's production and trade competitiveness in the face of international market competition and tap the potential for competition. This paper uses the General Administration of Customs' 2012–2022 statistical data to calculate four commonly used international competitiveness evaluation indicators: the market share index (MS index), the trade competitive advantage index (TC index), the Michaely fluctuation index (MI index), and the revealed comparative advantage index (RCA index). A longitudinal evaluation of the annual trends in the international competitiveness of China's manufacturing industry is then carried out. Combined with the above evaluation indicators, a comprehensive evaluation of each province's digital trade development level in China is carried out using the coefficient of variation method.

4.2.2. Weighting Based on the Coefficient of Variation

The coefficient of variation method solves the problems of subjectivity and differing units of indicators in weight calculation. The coefficient of variation method calculates the coefficient of variation of each indicator. It measures the fluctuation level of each indicator through variance and means to calculate each indicator's weight. The specific steps of the coefficient of variation method are as follows:

- (1) Calculate the Mean and Standard Deviation of Each Indicator

First, the average value $\bar{x}_i$ of the i^{th} indicator is calculated using Equation (21), where x_{ij} is the j^{th} observation of the i^{th} indicator, and n represents the number of observations.

$$\bar{x}_i = \frac{1}{n} \sum_{j=1}^n x_{ij} \quad (21)$$

Next, the standard deviation σ_i of the i^{th} indicator is calculated using Equation (22), where x_{ij} is the j^{th} observation of the i^{th} indicator, n represents the number of observations, and $\bar{x}_i$ is the average value of the i^{th} indicator.

$$\sigma_i = \sqrt{\frac{1}{n} \sum_{j=1}^n (x_{ij} - \bar{x}_i)^2} \quad (22)$$

(2) Calculate the Coefficient of Variation

According to Formula (23), the coefficient of variation V_i of the i^{th} index is calculated, where σ_i is the standard deviation of the i^{th} index, and $\bar{x}_i$ is the mean value of the i^{th} index.

$$V_i = \frac{\sigma_i}{\bar{x}_i} \quad (23)$$

(3) Calculate the Weight of Each Indicator

According to Formula (24), the weight W_i of the i^{th} indicator is calculated, where V_i is the coefficient of variation of the i^{th} indicator and m represents the number of indicators.

$$W_i = \frac{V_i}{\sum_{i=1}^m V_i} \quad (24)$$

4.2.3. Overall Evaluation

The weights of the four competitiveness indicators MS, TC, MI, and RCA for the manufacturing industry in 31 provinces, municipalities, and autonomous regions in China from 2012 to 2022 were calculated, as shown in Table 6. As can be seen from Table 6, the MS index has the most significant weight, followed by the TC index, MI index, and RCA index.

Table 6. Weights of the four indicators of China's manufacturing industry's international competitiveness, 2012–2022.

Year	MS Index	TC Index	RCA Index	MI Index
2012	0.57	0.13	0.16	0.14
2013	0.59	0.12	0.15	0.13
2014	0.57	0.12	0.16	0.15
2015	0.60	0.13	0.09	0.18
2016	0.63	0.15	0.09	0.14
2017	0.59	0.14	0.08	0.19
2018	0.55	0.14	0.08	0.24
2019	0.57	0.15	0.08	0.19
2020	0.59	0.17	0.09	0.14
2021	0.58	0.17	0.11	0.14
2022	0.60	0.17	0.12	0.11
Average	0.58	0.15	0.11	0.16

Data source: calculated and compiled by the author.

The coefficient of variation method was used to calculate the weights, the 2012–2022 China Manufacturing International Competitiveness Composite Index, and its ranking, as shown in Table 7. Table 7 shows that from 2012 to 2022, Guangdong, Jiangsu, and Zhejiang provinces consistently ranked as the top three in terms of the overall development of

China's manufacturing industry's international competitiveness, with Guangdong ranking highest in overall international competitiveness. This is closely related to these three provinces being central industrial provinces. Guangdong is known for manufacturing consumer electronics, Jiangsu is most vital for photovoltaics and semiconductors, and Zhejiang is important for manufacturing “industrial mother machines”, i.e., metal cutting machine tools, which are machines that manufacture machines. Xinjiang's oil, natural gas, and coal resources have driven the rapid development of China's manufacturing industry.

Table 7. Top 10 international competitiveness rankings and composite indices of China's manufacturing industry, 2012–2022.

Year	Ranking and Composite Index									
	1	2	3	4	5	6	7	8	9	10
2012	Guangdong 0.85	Jiangsu 0.64	Zhejiang 0.55	Hebei 0.44	Shanghai 0.44	Shandong 0.39	Ningxia 0.34	Inner Mongolia 0.34	Henan 0.34	Tianjin 0.33
2013	Guangdong 0.87	Jiangsu 0.58	Zhejiang 0.51	Hebei 0.42	Shanghai 0.40	Shandong 0.37	Henan 0.32	Fujian 0.31	Shanxi 0.30	Tianjin 0.29
2014	Guangdong 0.85	Jiangsu 0.59	Zhejiang 0.51	Hebei 0.45	Shandong 0.39	Shanghai 0.39	Henan 0.33	Tibet 0.33	Shanxi 0.32	Fujian 0.30
2015	Guangdong 0.82	Jiangsu 0.54	Zhejiang 0.51	Shanghai 0.38	Guangxi 0.36	Shandong 0.34	Fujian 0.32	Chongqing 0.31	Xinjiang 0.30	Jiangxi 0.27
2016	Guangdong 0.86	Jiangsu 0.57	Zhejiang 0.55	Shanghai 0.39	Shandong 0.35	Fujian 0.33	Xinjiang 0.32	Guangxi 0.31	Hebei 0.28	Chongqing 0.28
2017	Guangdong 0.82	Jiangsu 0.58	Zhejiang 0.53	Shanghai 0.37	Guangxi 0.37	Shandong 0.34	Fujian 0.32	Xinjiang 0.31	Hebei 0.30	Chongqing 0.27
2018	Guangdong 0.77	Jiangsu 0.58	Zhejiang 0.52	Guangxi 0.43	Shanghai 0.37	Shandong 0.33	Fujian 0.31	Hebei 0.30	Xinjiang 0.30	Chongqing 0.28
2019	Guangdong 0.83	Jiangsu 0.64	Zhejiang 0.60	Guangxi 0.41	Shanghai 0.40	Shandong 0.37	Fujian 0.37	Hunan 0.34	Tibet 0.33	Xinjiang 0.33
2020	Guangdong 0.88	Jiangsu 0.68	Zhejiang 0.68	Shandong 0.45	Shanghai 0.42	Fujian 0.40	Guangxi 0.38	Hunan 0.36	Chongqing 0.36	Anhui 0.36
2021	Guangdong 0.86	Jiangsu 0.69	Zhejiang 0.69	Shandong 0.47	Shanghai 0.41	Fujian 0.41	Chongqing 0.38	Jiangxi 0.37	Guangxi 0.37	Xinjiang 0.37
2022	Guangdong 0.86	Jiangsu 0.70	Zhejiang 0.70	Shandong 0.47	Shanghai 0.42	Fujian 0.39	Xinjiang 0.38	Hunan 0.36	Jiangxi 0.36	Anhui 0.35

Data source: calculated and compiled by the author.

5. Empirical Analysis of the Impact of Digital Trade on the International Competitiveness of China's Manufacturing Industry

5.1. Model Specification

Applying the theoretical analysis in the previous section and referring to the approach of Huang et al. (2023) [76], a benchmark regression model is constructed to test Hypothesis 1 and explore the impact of digital trade on the international competitiveness of China's manufacturing industry:

$$MIC_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (25)$$

In Equation (25), MIC_{it} is the level of international competitiveness of the manufacturing industry in province i in period t , DT_{it} is the level of digital trade development in province i in period t , X_{it} is the set of a series of control variables, α_0 is the intercept term, α_1 is the estimation parameter of core explanatory variables, α_2 is the estimation parameter of control variables, u_i is the fixed effect of province, λ_t is the time effect, ε_{it} is the random error term, i indicates the province, and t represents the year.

To test Hypotheses 2 and 3 and determine whether the foreign investment level (FDI) and scientific and technological research and development (R&D) variables play a mediating role in the process of digital trade promoting international competitiveness in the manufacturing industry, and considering the endogeneity problems that may arise when using the three-

step method of mediating effect model, this paper refers to the practices of Jiang (2022), Zhu et al. (2022), and Dell et al. (2010) [77–79]; the following model is constructed to investigate whether the FDI and R&D variables play a mediating role in the process of digital trade promoting the international competitiveness of the manufacturing industry:

$$M_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (26)$$

$$MIC_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (27)$$

M_{it} is the mediating variable, specifically referring to the level of foreign direct investment (FDI) and the capacity for scientific and technological research and development (R&D). Equation (25) represents the total effect model of the impact of digital trade on the international competitiveness of the manufacturing industry; Equation (26) describes the direct effect model of the impact of digital trade on the mediating variable; and Equation (27) incorporates digital trade and the mediating variable into the same model to examine the mediating effect of the mediating variable on the impact of digital trade on the international competitiveness of the manufacturing industry.

5.2. Variable Selection and Explanation

(1) Explained Variables

The study selects the manufacturing international competitiveness comprehensive indicator (MIC) as the explanatory variable to measure the international competitiveness of China's manufacturing industry; the specific measurement is described in the previous section.

(2) Core Explanatory Variables

This study selects the development level of digital trade (DT) as the core explanatory variable. The development level of digital trade is an essential engine for the high-quality development of the manufacturing industry, which is an important factor for the industry to have a competitive advantage in the international market. The specific measurement is also presented in the previous section.

(3) Control Variables

Considering the variables that will have an impact on the international competitiveness of a country's manufacturing industry according to the availability of data and with reference to the practices used in existing studies, this paper draws on the research of Huang et al. (2023) [76] and combines the factors that affect the international competitiveness of the manufacturing industry at the national and industry levels, selecting the following three variables as the control variables for this study:

① Human capital stock (HC): High-quality talent provides intellectual support for digital trade to promote the international competitiveness of the manufacturing industry. On the one hand, digital trade offers a digital platform for manufacturing enterprises to communicate and learn freely with the outside world, which helps to acquire the latest knowledge and skills needed by the enterprise and ultimately promotes the substantial improvement of staff's professional ability and quality. On the other hand, digital inputs optimize the human capital structure by squeezing out part of the low-skill labor force and increasing the demand for highly skilled labor, reducing the innovation inputs and increasing the innovation outputs to improve the innovation efficiency of manufacturing enterprises. Domestic scholars mostly use several alternative indicators based on income, human capital characteristics, average years of education, and so on to approximate human capital measurement. This study selects the average years of education per capita indicator to measure the level of human capital in each province and region.

② Logistics infrastructure (INF): Logistics infrastructure is the driving force enabling digital trade to promote the high-quality development of manufacturing. Optimized

and efficient urban infrastructure can also further reduce the cost of logistics transaction links and other direct flow costs between production and operation factors, enhance product competitiveness, improve the efficiency of resource integration, and thus promote manufacturing exports. This analysis uses the ratio of the sum of railway and highway mileage in each province to the region's land area to express logistics infrastructure. The larger the value, the higher the level of logistics infrastructure construction in the province.

③ Level of government regulation (GOV): Some of the manufacturing industries that have an impact on the national economy and people's livelihoods find it challenging to maintain their operations by market forces alone and require substantial government support, and the formulation of government policies has a particular impact on the enhancement of the international competitiveness of the manufacturing industry. This analysis adopts the ratio of local general public budget expenditure to regional GDP to express government regulation.

(4) Mediating Variables

① Level of foreign investment (FDI): This study uses the actual total foreign investment in the selected area to measure this indicator; the inflow of foreign capital not only enhances the capital mobility of the domestic market but also introduces foreign advanced production equipment management experience, allowing the domestic manufacturing industry to create a "technological spillover effect", which helps to improve the quality of China's manufacturing products, reduce enterprise production costs, and enhance the international competitiveness of manufacturing.

② Scientific and technological research and development capabilities (R&D): Digital trade has promoted the integration of digital technology and manufacturing, accelerating the transformation of old and new driving forces, and scientific and technological research and development can promote technological innovation. This is the intellectual guarantee and core driving force for digital trade to enhance the international competitiveness of the manufacturing industry. In this study, the indicator of full-time equivalent R&D personnel is selected to measure the intensity of scientific research personnel investment, expressed by R&D, representing the number of R&D personnel invested in each province. Considering the problem of heteroscedasticity, this variable is logarithmically processed in subsequent empirical analyses as shown in Table 8.

Table 8. Classification and description of variables.

Variable Category	Symbol	Variable Name	Description of Variable
Explained variables	MIC	International competitiveness of the manufacturing industry	Comprehensive evaluation by assigning weights to four commonly used international competitiveness evaluation indicators using the coefficient of variation method
Core explanatory variables	DT	Level of development of digital trade	Entropy weight TOPSIS combined measures
	HC	Human capital stock	Years of schooling per capita
Control variables	INF	Logistics infrastructure	Ratio of the sum of the number of railway and motorway miles operated in each province to the land area of the region
	GOV	Level of government regulation	The ratio of general budget expenditure to GDP
Mediating variables	FDI	Level of foreign investment	Total foreign investment
	RD	Scientific and technological research and development capacity	Full-time equivalent R&D personnel

Source: compiled by the author.

5.3. Data Source and Processing

Considering the availability of data for each variable and the consistency of statistical standards, this analysis uses panel data from 31 provinces, autonomous regions, and municipalities in China from 2012 to 2022. The trade data used in the measurement of

the international competitiveness of the manufacturing industry come from the General Administration of Customs. The data for the explanatory variables, control variables, and some intermediary variables come from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Economic Net Statistical Database, and the official website of the Ministry of Civil Affairs of the People's Republic of China.

5.4. Empirical Tests and Analysis of Results

5.4.1. Descriptive Statistics

Table 9 shows that the mean value of international competitiveness in manufacturing is 0.29, the minimum value is 0.004, and the maximum value is 0.88, which indicates that there are specific differences in the level of international competitiveness in manufacturing among different regions. The mean value of the level of digital trade is 0.19, the minimum value is 0.003, and the maximum value is 0.89, which shows that there are specific differences in the level of digital trade among different regions.

Table 9. Descriptive statistics.

Variable	N	Mean	SD	Min	Max
MIC	341	0.29	0.16	0.00	0.88
DT	341	0.19	0.19	0.00	0.89
HC	341	8.98	1.10	4.22	12.59
INF	341	0.07	0.05	0.01	0.22
GOV	341	0.28	0.21	0.11	1.38

Data source: calculated and compiled by the author.

5.4.2. Basic Regression Analysis

The general causes of endogeneity problems are mainly measurement bias and omitted variables. This study controls for potential endogeneity problems as much as possible when constructing the model. Regarding the problem of measurement bias, this study employs a comprehensive evaluation system for the level of development of digital trade and the international competitiveness of the manufacturing industry by using the entropy value method from the official statistical yearbook data to reduce the measurement error caused by the original data; to address the problem of omitted variables, three control variables, namely, logistics infrastructure, the level of foreign investment, and the level of governmental regulation, are added to the regression analysis. When choosing the model, the Hausman test was carried out, and the test results could not negate the original hypothesis that these models are the same. It can be assumed that the stochastic model better simulates the actual situation. Therefore, according to the test results, the panel fixed-effects model was finally chosen to regress Equation (9). STATA 17 software was used to verify the impact of digital trade and control variables on the international competitiveness of the manufacturing industry by adding control variables one by one, and Table 10 was obtained. Column (1) in Table 10 presents the results of the impact of digital trade on the improvement of the international competitiveness of the manufacturing industry, and columns (2)–(4) report the results of the impact of digital trade on the international competitiveness of manufacturing industry after adding HC, INF, and GOV control variables one by one.

Table 10. Base regression results.

Variable	(1) MIC	(2) MIC	(3) MIC	(4) MIC
DT	0.45 *** (0.12)	0.45 *** (0.13)	0.44 *** (0.12)	0.44 *** (0.12)
HC		−0.01 (0.02)	−0.00 (0.02)	−0.01 (0.02)
INF			−0.15 * (0.07)	−0.16 ** (0.08)
GOV				−0.01 (0.02)
Constant	−0.07 (0.07)	0.02 (0.19)	−0.00 (0.19)	0.01 (0.19)
Observations	341	341	341	341
R-squared	0.93	0.93	0.93	0.93
ID FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As the control variables are added, the digital trade (DT) coefficients remain positive, at 0.45, 0.45, 0.44, and 0.44, respectively. The impact of digital trade on the international competitiveness of the manufacturing industry is positive at the 1% significance level after the HC, INF, and GOV variables are added, which indicates that after excluding the influence of other factors, the role of digital trade in enhancing the international competitiveness of the manufacturing industry is still significant, verifying Hypothesis 1.

The regression results of models (2) to (4) also prove that the impact of digital trade (DT) on the international competitiveness of the manufacturing industry is robust under different control variable conditions. Regarding control variables, the coefficient of human capital stock (HC) on the international competitiveness of the manufacturing industry is −0.01 and is not significant. A possible reason is that as the number of years of education increases, the workforce tends to engage in industries and positions with higher added value, such as the service industry or scientific research and development. In addition, the manufacturing industry, especially traditional manufacturing, often requires skilled workers. Excessive years of education do not necessarily match the actual skill requirements of manufacturing jobs. More years of education do not necessarily mean people have the practical skills required by the manufacturing industry. Logistics infrastructure (INF) has a negative impact on the international competitiveness of the manufacturing industry. The Chinese manufacturing industry relies heavily on the export market. Its international competitiveness is more affected by external market demand and less by domestic infrastructure construction. Moreover, the debt accumulation resulting from the construction of infrastructure such as railways and roads may have a crowding-out effect on the government's investment in the development of the manufacturing industry, thus influencing the international competitiveness of the manufacturing industry. The level of government regulation (GOV) has a negative impact on the international competitiveness of the manufacturing industry. Viewing the original data reveals that local general public expenditure has increased year by year. However, its share of GDP has decreased year by year. In contrast, the level of development of the manufacturing industry is rising year by year, indicating that the development of China's manufacturing industry is gradually freeing itself from government financial support, adapting to the development environment of the market mechanism, and reflecting the decisive role of the market mechanism in the development of China's manufacturing industry. Financial support should focus on

optimizing structure, supporting large-scale manufacturing projects related to the country's economy and people's livelihood, and enhancing the government's role in macro-control.

5.4.3. Robustness Test

(1) Endogeneity Issues

Endogeneity is a critical issue in economic research that must be addressed. In this paper, the enhancement of manufacturing international competitiveness is inseparable from the rapid development of digital trade. Conversely, the growth of digital trade is also contingent upon an improvement in manufacturing competitiveness. Therefore, a causal endogeneity relationship exists between the level of digital trade and the international competitiveness of manufacturing. Moreover, numerous factors influence the international competitiveness of manufacturing, and the control variables in this paper may not fully prevent omitted variable bias. Thus, the empirical analysis of the impact of digital trade on manufacturing competitiveness may suffer from bidirectional causality and omitted variable bias. This analysis attempts to alleviate the endogeneity problem by employing the instrumental variable (IV) method.

The development of the Internet in various regions has served as a foundation for the growth of digital trade, and the advancement of internet technologies can be traced back to the widespread adoption of landline telephones. Before the proliferation of landline phones, communication infrastructure was relatively underdeveloped, and the flow of information was slow, especially in areas far from major cities. The introduction of landline telephones not only enhanced communication efficiency but also laid the groundwork for the further spread of the Internet. Therefore, there exists a potential positive correlation between the penetration of landline telephones and the development of digital trade, particularly in regions with limited infrastructure.

Before the widespread use of landlines, postal services played a crucial role in information dissemination and, to some extent, acted as the executor of government initiatives to develop communication networks. Thus, the distribution and density of post offices were historically linked to the penetration of landline phones, indirectly influencing the speed of digital trade adoption. For instance, in areas with a dense network of post offices, communication infrastructure was typically more developed, and the public's demand for and receptiveness to information exchange were higher, which created favorable conditions for the application of internet technologies and the development of digital trade.

By treating the number of landline phones and post offices as instrumental variables, we can effectively address endogeneity issues. Both the penetration of landline phones and the number of post offices are closely linked to the development of digital trade, and they indirectly influence digital trade development by promoting the advancement of internet infrastructure. Over time, however, changes in the number of landlines and post offices no longer directly impact the current competitiveness of the manufacturing industry, particularly in the context of rapid advancements in information technology. The impact of these variables is mainly reflected in their early influence on the development of digital trade infrastructure. As such, the number of landline phones and post offices can serve as exogenous instrumental variables that help predict the development of digital trade without directly interfering with changes in other industries or economic structures.

Therefore, adopting the method of Zhu et al. (2024) [80] and Huang et al. (2019) [81], we construct interaction terms between the number of landline phones per hundred people and the number of post offices per million people in 1984, along with the broadband access numbers from the previous year. This approach more effectively captures the long-term impact of early communication infrastructure on digital trade development. The regression results using the instrumental variables method are shown in Table 11. Columns (2) and (4)

indicate that after using the instrumental variables, the estimated coefficients for digital trade are significantly positive at the 1% level. Additionally, the results of the KP rk LM and KP rk Wald F-statistics suggest that the selected instrumental variables are reasonable and effective.

Table 11. Results of endogenous problem handling.

Variable	(1) DT	(2) MIC	(3) DT	(4) MIC
iv1	0.00 *** (0.00)			
iv2			0.00 *** (0.00)	
DT		0.80 *** (0.04)		1.15 *** (0.09)
Constant	−0.19 (0.15)	0.62 *** (0.14)	−0.73 *** (0.21)	0.94 *** (0.23)
ID FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Observations	341	341	341	341
R-squared	0.50	0.61	0.34	0.40
KP rk LM		64.16 [0.00]		37.06 [0.00]
KP rk Wald F		59.89 {16.38}		27.09 {16.38}

Robust standard errors in parentheses. *** $p < 0.01$.

(2) Other Robustness Tests

In order to ensure the reliability of the estimation results in this paper, the following methods are used for robustness tests: First, the dependent variable is replaced for robustness testing. To enhance the robustness of the results, we decided to substitute the dependent variable in the robustness check. As indicated by the previous calculation of China's manufacturing competitiveness indicators, the weight of the RCA index is the smallest among the four competitiveness indicators. Therefore, by excluding RCA, which has a relatively low weight, we reconstructed the evaluation system. This approach examines whether the remaining indicators can collectively support the impact of digital trade on the international competitiveness of manufacturing. This further validates the stability and consistency of the conclusions across different model specifications. Table 11 (1) shows the regression results indicating that the coefficient of influence of the level of development of digital trade is significantly positive, which means that after excluding the RCA index, the development of digital trade has a significant positive impact on the international competitiveness of the manufacturing industry, indicating that the results of the benchmark regression are robust. Second, a robustness check is conducted by reducing the sample size. Due to the relatively low values of Gansu Province and the Tibet Autonomous Region, as well as significant differences in their economic structures and geographical conditions compared to those of the other provinces, both Gansu and Tibet are excluded from the robustness test. In Table 12 (2), the relationship between digital trade and the international competitiveness of the manufacturing industry remains significantly positive, and the results of the benchmark regression are robust. Third, we replace the core explanatory variable with one lagged period for the level of digital trade development. Considering that the impact of digital trade development on China's international competitiveness in the manufacturing industry may have a lag, this analysis replaces the explanatory variable with one lagged period for the level of digital trade development (DT-LAG) to conduct a

robustness test. The results are shown in Table 12 (3). The results show that the impact coefficient of the lagged one-period digital trade development level on China's manufacturing industry's international competitiveness is still significantly positive, indicating that the benchmark regression results are robust. Fourth, considering the significant impact of the COVID-19 outbreak on the global economy in 2020, and in order to avoid the negative impact of the COVID-19 pandemic, this paper excludes the samples from 2020 to 2022 to test the robustness of the results. The results are shown in Table 12 (4), which shows that after excluding these particular years, the impact coefficient of the level of development of digital trade on the international competitiveness of China's manufacturing industry is still significantly positive, indicating the robustness of the benchmark regression results. Fifth, the system GMM model can effectively overcome the endogeneity problem between variables and better capture the dynamic interactions between variables. Table 12 (5) shows the measurement results of the system GMM model, where AR (1) is less than 0.2 and AR (2) is more significant than 0.1, indicating that the model has a first-order autocorrelation is significant; moreover, there is no second-order autocorrelation, and the p -values of the Hansen test and the Sargan test both exceed 0.1, indicating that the instrumental variables are valid and the test for overidentification passes. The measurement results of the system GMM model are reliable. The regression results show that the impact coefficient for the level of development of digital trade on the international competitiveness of China's manufacturing industry is still significantly positive. In short, regardless of the form of robustness test used, the regression results are consistent with the benchmark regression results, indicating that the impact of digital trade on the international competitiveness of the manufacturing industry passed the robustness test and also fully demonstrating that digital trade can significantly enhance the international competitiveness of China's manufacturing industry.

Table 12. Robustness test of the impact of digital trade on the international competitiveness of China's manufacturing industry.

Variable	(1) Substitution of Explanatory Variables	(2) Reduced Sample	(3) One-Period Lag	(4) Elimination of Special Years	(5) GMM
DT	0.35 *** (0.11)	0.41 *** (0.12)		0.49 *** (0.16)	0.43 *** (0.16)
L.dt			0.22 * (0.13)		
L.mic					1.03 *** (0.12)
Constant	−0.01 (0.22)	−0.07 (0.37)	0.12 (0.28)	1.03 *** (0.38)	0.43 ** (0.18)
ID FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
Observations	341	319	310	248	310
R-squared	0.96	0.94	0.94	0.93	
AR (1)					0.02
AR (2)					0.11
Sargan					0.62
Hansen					0.59

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In order to explore the effectiveness of the digital trade development evaluation system, relevant data from 31 provinces in mainland China from 2012 to 2022 were used.

Cronbach's alpha coefficient method was selected for a reliability test and analysis of the constructed digital trade development evaluation system. First, the indicator data were processed into a dimensionless form to ensure their values were between 0 and 1. Second, the dimensionless processed indicator system was analyzed using STATA software for reliability tests. The test results are shown in Table 13. The test results show that the reliability coefficients of the China Digital Trade Development Evaluation System and Cronbach's alpha coefficients based on standardization are 0.95 and 0.96, respectively, above 0.9. Therefore, it can be concluded that the constructed evaluation system has good and highly reliable internal reliability. The results calculated based on this index system can provide a reasonable interpretation of the China Digital Trade Development Evaluation System.

Table 13. Reliability testing.

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Terms
Average interitem correlation	0.51	0.59
Number of items in the scale	18	18
Scale reliability coefficient	0.95	0.96

Data source: calculated and compiled by the author.

5.4.4. Heterogeneity Test

Due to the regional disparities in development levels across China, the sample data are divided into eastern, central, and western regions based on the classification by the National Bureau of Statistics and China's regional economic divisions (The eastern region refers to the 11 provinces (municipalities) of Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, and Liaoning; the central region refers to the 8 provinces of Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Jilin, and Heilongjiang; and the western region refers to the 12 provinces (autonomous regions and municipalities) of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang). This segmentation aims to examine the regional heterogeneity of digital trade's impact on China's manufacturing industry's international competitiveness. The analysis further explores whether this impact varies across different regions and performs a heterogeneity test. The results of the test (see Table 14) show that digital trade significantly promotes manufacturing international competitiveness in all three regions, with the strongest effect in the eastern region and the weakest in the western region.

Table 14. Heterogeneity analysis.

Variable	(1) Nationwide	(2) Eastern Region	(3) Central Region	(4) Western Region
DT	0.42 *** (0.12)	0.72 *** (0.04)	0.60 *** (0.18)	0.44 *** (0.09)
Constant	0.06 (0.29)	1.98 *** (0.33)	1.68 *** (0.58)	0.15 (0.12)
Observations	341	121	88	132
R-squared	0.93	0.78	0.47	0.16
ID FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** $p < 0.01$.

The reasons for this variation are as follows:

(1) Regional Disparities in Digital Technology and Infrastructure

The eastern region leads in digital technology development, 5G network coverage, and cloud computing infrastructure. In contrast, the central and western regions face delays in digital infrastructure development (such as insufficient internet bandwidth and sparse data centers), limiting the potential for digital trade to improve manufacturing efficiency.

In terms of digital technology applications, the eastern region has developed digital industry clusters, particularly in the Yangtze River Delta and Pearl River Delta, centered around e-commerce and industrial internet usage. These regions can leverage real-time data analysis and supply chain optimization to significantly enhance international competitiveness. In comparison, the central and western regions have lower manufacturing digitalization penetration and still rely primarily on traditional production models, hindering their ability to fully capitalize on digital trade's cost-reducing and efficiency-enhancing benefits.

(2) Economic Development and Market Environment Disparities

The eastern region has a larger economy and more active consumer markets, providing the demand necessary for the integration of digital trade with manufacturing. By contrast, the central and western regions, constrained by smaller market sizes and lower purchasing power, face difficulties in expanding international orders via digital trade, resulting in slower improvements in competitiveness.

(3) Regional Imbalances in Policy Support and Openness

The eastern region introduced digital trade-specific policies earlier (e.g., the "Digital Free Trade Zone" pilot in Zhejiang) and attracted digital platform companies through tax incentives. In contrast, the implementation of such policies in the Central and Western regions has been slower, and local governments have limited fiscal capacity, making it difficult to match the eastern region's investments in digital infrastructure and R&D subsidies. Coastal provinces in the eastern region also benefit from their port and international trade hub status, facilitating easier connections to global markets via digital trade platforms, thereby reducing logistics and information costs. However, the central and western regions are constrained by geographical distances and incomplete cross-border logistics networks, which reduce the "borderless" advantages of digital trade.

(4) Regional Concentration of Talent and Innovation Resources

The eastern region accounts for over 70% of the country's digital technology talent, with its innovation capabilities directly driving manufacturing toward intelligence and service-oriented models. In contrast, the central and western regions face talent loss issues, which lead to the slower adoption of digital technologies. Additionally, the eastern region has a dense network of universities and research institutions (such as those in Beijing and Shanghai), accelerating the industrialization of digital technologies through industry–academia–research collaborations. The Central and Western regions, on the other hand, have weaker linkages between industry, academia, and research, resulting in lower rates of technology commercialization and restricting the deeper impact of digital trade on manufacturing competitiveness.

Thus, the structural differences in digital technology, economic foundations, policy support, and talent reserves between the eastern, central, and western regions are the fundamental reasons for the varying effects of digital trade on manufacturing international competitiveness.

5.4.5. Mediating Effect Test

Based on Formulas (26) and (27) of the mediating effect model, this paper explores the mediating role of the level of foreign direct investment (FDI) and the capacity for scientific and technological research and development (R&D) in the process of digital trade (DT) influencing the international competitiveness of the manufacturing industry (MIC). As shown in Table 15, Model (1) presents the results of the benchmark regression; Models (2)–(3) show the regression results with the level of foreign direct investment (FDI) as the

mediating variable. Specifically, Model (2) examines the impact of digital trade on the level of foreign direct investment, and Model (3) examines the impact of digital trade combined with the level of foreign direct investment on the international competitiveness of the manufacturing industry. Models (4)–(5) show the regression results with the capacity for scientific and technological research and development (R&D) as the mediating variable. Here, Model (4) examines the impact of digital trade on the capacity for scientific and technological research and development, and Model (5) examines the impact of digital trade combined with scientific and technological research and development capabilities on the international competitiveness of the manufacturing industry.

Table 15. Mediated effects test.

Variable	(1) MIC	(2) lfdi	(3) MIC	(4) lrd	(5) MIC
DT	0.42 *** (0.12)	4.80 *** (1.27)	0.36 *** (0.12)	2.98 *** (0.58)	0.27 ** (0.13)
lfdi			0.01 ** (0.01)		
lrd					0.05 ** (0.02)
Constant	0.06 (0.29)	−2.42 (2.19)	0.09 (0.28)	9.33 *** (0.61)	−0.42 (0.36)
Observations	341	341	341	341	341
R-squared	0.93	0.95	0.93	0.99	0.93
ID FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

The results show that in Model (2), digital trade positively and significantly affects the level of foreign investment; moreover β_1 , γ_1 , and γ_2 in Model (3) are all significant, and γ_1 and $\beta_1\gamma_2$ are of the same sign, so it can be assumed that there is a partially mediated effect, i.e., digital trade can directly promote the international competitiveness of the manufacturing industry and can also enhance the international competitiveness of the manufacturing industry by attracting foreign investment. Therefore, Hypothesis 2 is established. Model (4) shows that digital trade positively and significantly affects scientific and technological R&D capacity, and Model (5) shows that both digital trade and scientific and technological R&D capacity positively and significantly affect the international competitiveness of the manufacturing industry. This shows that scientific and technological research and development capabilities play a partial mediating role between digital trade and the high-quality development of the manufacturing industry, thus verifying Hypothesis 3. In summary, Hypothesis 2 and Hypothesis 3 are established to show that introducing digital trade into the process of foreign investment, science, and technology R&D can enable the region to fully enjoy capital dividends and technological dividends, which represents the optimal role of digital trade and promotes the international competitiveness of the manufacturing industry.

The results of the mediation effect test align with the transaction cost theory and Moore's Law. The application of digital technologies facilitates the decentralization of enterprises and the reduction in transaction costs by activating latent data, accurately matching supply and demand, and addressing information asymmetries. This, in turn, reduces ineffective investments and production, thereby enhancing manufacturing productivity. According to Moore's Law, technological advancements lower the cost of digital technologies, which effectively reduces trial-and-error costs for enterprises; enhances their ability to acquire, imitate, and transform resources and technologies; and drives technologi-

cal innovation in manufacturing. As a result, the rapid development of digital trade can improve the international competitiveness of manufacturing by attracting foreign direct investment (FDI) and advancing technological research and development.

5.5. Spatial Econometric Modeling

5.5.1. Research Method

(1) Defining Research Objectives and Model Framework

Due to the significant spatial heterogeneity in the international competitiveness of the manufacturing industry and the level of digital trade development across different regions in China, it is essential to select an appropriate spatial econometric model that accounts for regional interactions and geographical adjacency. Therefore, constructing a spatial econometric model is necessary to assess the specific direction and magnitude of the effects.

(2) Defining Variables and Spatial Weight Matrix

Dependent Variable: The international competitiveness of the manufacturing industry in various regions. **Independent Variables:** These include the level of digital trade development and other factors influencing the competitiveness of the manufacturing industry. **Spatial Weight Matrix:** This matrix reflects the spatial relationships between regions, indicating the degree of geographic proximity or interaction.

(3) Testing for Spatial Autocorrelation

The selection of a spatial econometric model depends on the characteristics of spatial autocorrelation and errors. To determine whether spatial autocorrelation exists in the data, a spatial correlation test is conducted, with the Moran's I test being the classical method for assessing spatial autocorrelation. The Moran's I value is calculated to determine whether spatial clustering effects are present in the sample data. If Moran's I is significantly different from zero, it indicates the presence of spatial autocorrelation. In spatial data analysis, spatial autocorrelation suggests that the observations in one region may be influenced by neighboring regions. If the Moran's I test reveals spatial autocorrelation, the next step is to consider using a spatial econometric model.

(4) Selecting the Appropriate Spatial Econometric Model

Common spatial econometric models include the spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The LM test and Wald test can be used to further determine which spatial model to apply. The LM test helps to identify whether spatial effects need to be incorporated and whether a spatial lag term is required. Specifically, the LM test has two important versions: LM-Lag (to test for the need for a spatial lag term) and LM-Error (to test for the need for a spatial error term). If the LM test indicates a significant spatial lag effect, the SAR model should be chosen; if it suggests a significant spatial error effect, the SEM is appropriate. The Wald test is used to assess whether the model parameters are significant. This is crucial for validating spatial econometric models, particularly after selecting the appropriate model. The Wald test can also be used to further validate the impact of spatial spillover effects. When the LR statistic and Wald statistic are tested, if the results show the rejection of the null hypothesis, this implies that neither simple spatial lag effects nor spatial error effects can explain the data. This suggests that the more complex spatial Durbin model (SDM) is needed, as it can capture the spatial interdependencies between both the dependent and independent variables.

(5) Model Estimation and Result Analysis

After selecting the appropriate spatial econometric model, it is employed using econometric software (e.g., Stata). The analysis focuses on the impact of digital trade development on the international competitiveness of the manufacturing industry. Furthermore, based on

the results of spatial spillover effects, the influence of digital trade on the competitiveness of manufacturing in neighboring regions is explored.

5.5.2. Model Construction

In order to fully consider the impact of spatial factors, a spatial econometric model is constructed to explore the impact of the level of development of digital trade on the international competitiveness of the manufacturing industry. The specific model is as follows:

$$Y = \rho WY + \beta X + \theta WX + \mu \quad (28)$$

$$\mu = \lambda W\mu + \varepsilon, \varepsilon \sim N[0, \sigma^2 I] \quad (29)$$

In Equations (28) and (29), Y represents the explained variables; X represents all the explanatory variables; w represents the $n \times n$ dimensional geographic adjacency matrix, the elements W_{ij} of which are assigned a value of 1 if region i is adjacent to region j or assigned a value of 0 if region i is not adjacent to region j ; β represents the correlation coefficient of X ; ρ and θ represent the spatial correlation coefficients; λ represents the coefficient of spatial error; and μ and ε represent the stochastic errors, where ε follows a normal distribution. $\rho \neq 0, \theta = 0$, and $\lambda = 0$ conform to the spatial autoregressive model (SAR); $\rho = 0, \theta = 0$, and $\lambda \neq 0$ conform to the spatial error model (SEM); and $\rho \neq 0, \theta \neq 0$, and $\lambda = 0$ conform to the spatial Durbin model (SDM). Subsequently, the model form should be explicitly chosen according to the test and significance results.

5.5.3. Empirical Analysis

(1) Spatial Correlation Test

① Global Moran's index. This paper uses the global Moran's index to test for spatial autocorrelation in the international competitiveness of the manufacturing industry and the level of development of digital trade in 31 provinces from 2012 to 2022 (see Table 16). The value of the global Moran's index falls in the range $[-1, 1]$, with positive values indicating positive spatial correlation and negative values indicating negative spatial correlation. From 2012 to 2022, the Moran's index fluctuated. However, it was positive in all cases. It passed the significance test in all cases, indicating that the international competitiveness of the manufacturing industry and the level of development of digital trade have significant positive spatial correlation characteristics. Therefore, as a whole, the spatial correlation is significant, and it is appropriate to choose a spatial econometric model.

Table 16. Overall Moran's index for the international competitiveness of the manufacturing industry and the level of development of digital trade.

Year	MIC			DT		
	Moran's I	Z-Value	p-Value	Moran's I	Z-Value	p-Value
2012	0.15	1.92	0.06	0.21	2.27	0.02
2013	0.18	2.26	0.02	0.19	2.12	0.03
2014	0.16	2.05	0.04	0.19	2.09	0.04
2015	0.23	2.88	0.00	0.18	1.99	0.05
2016	0.24	3.00	0.00	0.20	2.25	0.02
2017	0.27	3.29	0.00	0.20	2.26	0.02
2018	0.26	3.06	0.00	0.19	2.17	0.03
2019	0.30	3.50	0.00	0.19	2.12	0.03
2020	0.35	3.95	0.00	0.20	2.21	0.03
2021	0.35	3.96	0.00	0.20	2.21	0.03
2022	0.33	3.81	0.00	0.19	2.12	0.03

Data source: calculated and compiled by the author.

② Local Moran's index. In order to examine the degree of spatial correlation in a particular region, this paper presents a local Moran diagram of the international competitiveness of manufacturing and the development level of digital trade. Due to space reasons, only the results of two years, 2012 and 2022, are reported. In Figures 1 and 2, it can be seen that most of the points corresponding to the Moran's index of the international competitiveness of the manufacturing industry and the level of development of digital trade among provinces are distributed in the first and third quadrants; i.e., provinces have a solid positive promotional effect in the local space, which is the same as that of the test results of the global Moran's index. From 2012 to 2022, the number of provinces that fall into the first quadrant and the third quadrant of the number of provinces increased, reflecting the increased degree of correlation between the international competitiveness of manufacturing and the level of digital trade development in the local space. Therefore, the local spatial positive correlation feature is significant, the spatial factor influence should be considered, and the spatial measurement model should be selected.

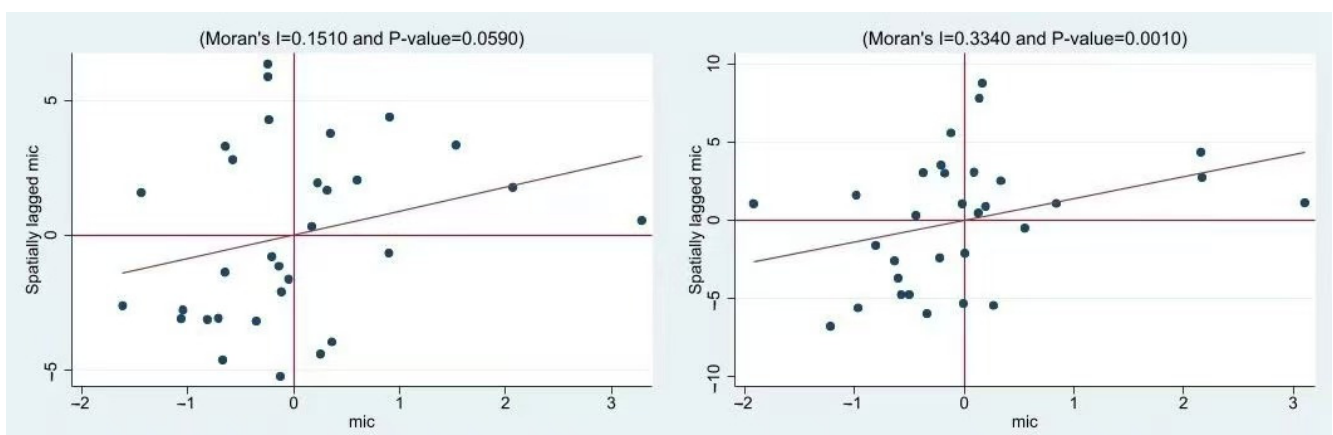


Figure 1. Localized Moran diagram of international competitiveness of manufacturing industries, 2012 and 2022.

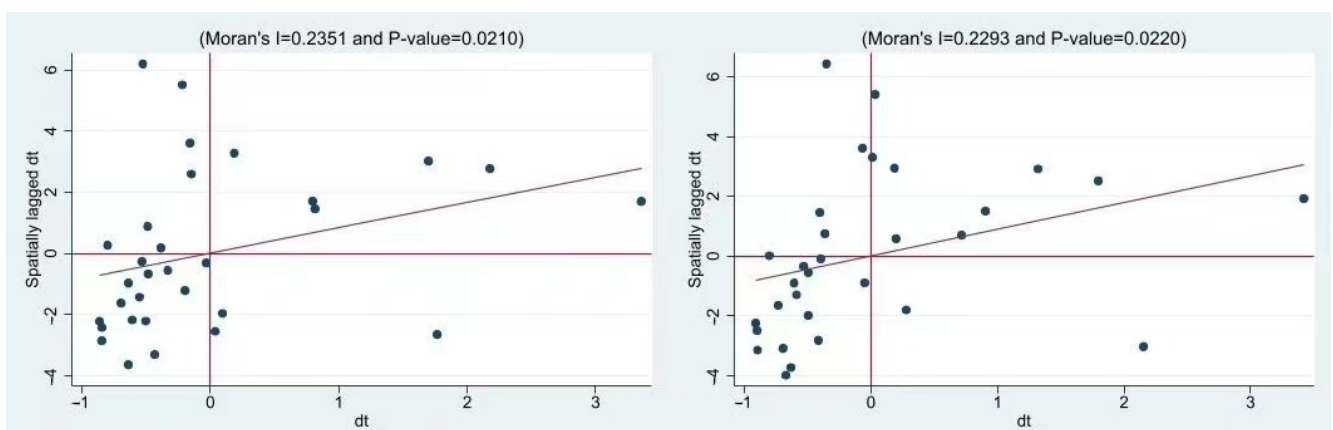


Figure 2. Localized Moran diagram of the level of development of digital trade, 2012 and 2022.

(2) Selection of a Spatial Econometric Model and Empirical Results

As seen from the previous section, there is a significant spatial correlation between international competitiveness in manufacturing and the level of development of digital trade. By establishing a spatial econometric model, the specific direction and magnitude of the impact of the level of development of digital trade on international competitiveness in manufacturing can be more accurately measured.

Table 17 presents the results of the spatial econometric model selection. First, the LM test was conducted to determine the type of spatial effects, which informed the choice of the appropriate model. The results showed that both the LM-Lag and LM-Error values were significant. In the subsequent robustness check, the robust LM-Error value was not significant, while the robust LM-Lag value was significant at the 1% level. This suggests that the spatial lag model is more suitable for this analysis. Next, based on the Hausman test results ($\text{Prob} \geq \chi^2 = 0.038$), the fixed-effects model was selected. Both the LR statistic and the Wald statistic rejected the null hypothesis, indicating that the spatial Durbin model (SDM) could not be simplified to either the spatial autoregressive model (SAR) or the spatial error model (SEM). Therefore, the SDM with time-fixed effects was ultimately chosen. The inclusion of time-fixed effects was necessary due to potential temporal dependencies in the data, where the effects at each time point may differ. Time-fixed effects help control for heterogeneity across different periods and account for the influence of external factors such as policy changes and market fluctuations. The SDM is regarded as the most comprehensive spatial econometric model because it accounts for the spatial lag effects of both the dependent and independent variables, allowing for a more accurate representation of spatial dependence and spillover effects. This makes it better suited for explaining and predicting the impact of digital trade on the international competitiveness of the manufacturing industry.

Table 17. Results of the spatial measurement selection.

Test	Result	<i>p</i> -Value
LM-Error test	2.97	0.09
Robust LM-Error test	1.42	0.23
LM-Lag test	31.56	0.00
Robust LM-Lag test	30.02	0.00
LR_spatial_lag	19.36	0.00
LR_spatial_error	9.01	0.03
Wald_spatial_lag	21.70	0.00
Wald_spatial_error	11.28	0.02

Data source: calculated and compiled by the author.

This series of tests and model selection ensures that the spatial econometric model effectively explains and predicts the spatial impacts of digital trade development on the international competitiveness of manufacturing while revealing the interactive relationships between different regions.

The benchmark regression of the spatial econometric model is shown in Table 18. The regression coefficient of China's digital trade development is 0.73. It is significant at the 1% significance level, indicating that the development of digital trade in the province has enhanced the international competitiveness of the manufacturing industry in the province. The coefficient of the spatial lag term of the digital trade level is 0.37. It passes the hypothesis test at the 1% significance level, indicating that the spatial effect of digital trade is significant. The development level of digital trade in this region also significantly promotes the international competitiveness of the manufacturing industry in other regions.

Table 19 shows the results of the spatial effect decomposition. The direct effect is the impact of digital trade on the level of development of digital trade and the international competitiveness of the region's manufacturing industry. In contrast, the indirect effect refers to the impact of the development of digital trade in the region on the international competitiveness of the manufacturing industry in neighboring regions. As can be seen from the table, the spatial direct effect, spatial indirect effect, and total effect of the level of development of digital trade are all significantly positive, indicating that the development

of digital trade in the province can promote the improvement of the international competitiveness of the province's manufacturing industry and also has a significant spatial spillover effect. The international competitiveness of the manufacturing industry in neighboring areas will also benefit as a result.

Table 18. Regression results of the spatial Durbin model.

Variable	(1) SDM Main	(2) SDM W _x
DT	0.73 *** (0.03)	0.37 *** (0.08)
HC	−0.30 *** (0.05)	−0.12 (0.09)
GOV	−0.04 * (0.02)	0.00 (0.03)
inf	−0.01 (0.01)	−0.00 (0.02)
rho		−0.34 *** (0.09)
Sigma2_e		0.01 *** (0.00)
Observations		341
R-squared		0.71
N		31

Standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

Table 19. Decomposition affect test results based on the SDM.

Variable	(1) SDM Direct	(2) SDM Indirect	(3) SDM Total
DT	0.73 *** (0.03)	0.09 *** (0.03)	0.82 *** (0.03)
HC	−0.31 *** (0.05)	−0.01 (0.07)	−0.32 *** (0.06)
GOV	−0.03 * (0.02)	0.01 (0.03)	−0.02 (0.02)
inf	−0.01 (0.01)	0.00 (0.02)	−0.01 (0.01)
rho		−0.34 *** (0.09)	
Sigma2_e		0.01 *** (0.00)	
Observations		341	
R-squared		0.71	
N		31	

Standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

6. Discussion

This study utilizes panel data from China's 31 provinces, autonomous regions, and municipalities directly under the central government to examine the impact of digital trade on the international competitiveness of the manufacturing industry. The results indicate that digital trade has significantly enhanced the international competitiveness of China's manufacturing industry, with this relationship demonstrating notable differences across

regions and through different channels of influence. The following is an in-depth analysis and discussion of the research findings.

First, this study reveals a significant positive impact of digital trade on the international competitiveness of manufacturing, a finding that has been thoroughly validated through robustness tests. This result not only aligns with mainstream perspectives in current literature but also expands the framework for understanding the role of digital trade in manufacturing development. Previous literature has predominantly focused on traditional trade factors such as tariff policies, trade agreements, and factor endowments and their effects on manufacturing. For instance, Xiong et al. (2017) [82] highlighted the direct impact of trade policy adjustments on manufacturing. In contrast, this study focuses on the emerging force of digital trade, highlighting how it facilitates information flow and technology spillovers by providing more efficient and cost-effective transaction platforms. Furthermore, digital trade effectively lowers the barriers for manufacturing enterprises to enter international markets, thereby enhancing the global competitiveness of the manufacturing industry. This finding not only demonstrates that digital trade has provided new momentum for the internationalization of China's manufacturing industry but also offers a theoretical foundation for the digital transformation of traditional manufacturing. Furthermore, it provides valuable insights for the international development of emerging industries. To this end, the government should actively promote the development of digital infrastructure, encourage the growth of cross-border e-commerce, and improve information flow efficiency. These measures will help further foster the healthy development of digital trade and enhance the international competitiveness of the manufacturing industry.

Second, the heterogeneity analysis in this study reveals significant regional differences in the impact of digital trade on the competitiveness of the manufacturing industry. The results show that the positive effects are strongest in the eastern region, while the effects in the central and western regions are relatively weak. This finding provides a theoretical basis for understanding the varying impacts of digital trade on manufacturing development across different regions. The reason digital trade has been able to quickly establish itself and play a crucial role in the eastern region is due to the region's relatively well-developed infrastructure, advanced information technology industry, and strong innovation capabilities. These factors, collectively, have facilitated the formation of efficient logistics systems, convenient information flow, and relatively mature digital platforms, enabling manufacturing enterprises in the eastern region to access global market demand, resources, and technological support in a shorter time frame. This undoubtedly provides strong support for the internationalization of the region's manufacturing industry. However, compared to that in the eastern region, the development of digital trade in the central and western regions lags behind. While there remains untapped potential for digital trade in these regions, and they may experience growth opportunities with the push of relevant policies, the current insufficient infrastructure, lower penetration of information technology, and limited market access hinder the digital transformation of manufacturing in these regions, making their global competitiveness relatively weak. Therefore, the analysis results of this study offer important implications for future policy-making. In the process of promoting digital trade development, policymakers need to pay greater attention to the regional differences in policy design and focus on implementing more targeted support measures tailored to the specific conditions of different regions. For the central and western regions, it is essential to increase investment in digital infrastructure, enhance the penetration of information technology, strengthen enterprise technical training, and develop cross-border e-commerce platforms. These measures will help narrow the regional development gap, effectively promote the widespread adoption of digital trade across different regions, and ultimately enhance the competitiveness of the manufacturing industry nationwide.

Third, this study shows that digital trade not only has a direct impact on enhancing the international competitiveness of the manufacturing industry but also exerts an indirect influence by attracting foreign investment and boosting research and development capabilities. On the one hand, digital trade provides foreign investors with more accessible investment opportunities and expanded market access, thus facilitating more efficient foreign direct investment (FDI) in China's manufacturing industry. The inflow of foreign capital injects advanced technologies and management experience into China's manufacturing industry, driving technological upgrades and improving its global competitiveness and industrial added value. On the other hand, digital trade plays a key role in enhancing the vitality and dynamism of local innovation systems by facilitating the rapid flow of information and technology. The establishment of digital platforms and the convenience of information flow allow enterprises to access global technology and market information more promptly, thereby enhancing their innovation capabilities and technological research and development levels. This further promotes the integration of technological R&D and product innovation, strengthening China's manufacturing industry's competitiveness in the global value chain. This finding carries significant implications for policy-making. While promoting the development of digital trade, the government should focus on simultaneously advancing foreign investment and technological innovation to create a virtuous cycle. The government should not only optimize the investment environment and guide foreign investment toward high-tech, high-value-added sectors but also intensify support for the innovation system to enhance the capacity for independent R&D by enterprises. Particularly in the context of the ongoing restructuring of global industrial chains, the government needs to coordinate policies across various domains to ensure that digital trade can maximize its potential in attracting foreign investment, fostering technological innovation, and improving enterprise competitiveness. This will ultimately promote the sustained growth and improvement of China's manufacturing industry in the global market.

Fourth, this study explores the spatial spillover effects of digital trade on the international competitiveness of the manufacturing industry. The findings reveal that digital trade not only enhances the competitiveness of manufacturing within a province but also promotes the competitiveness of neighboring provinces' manufacturing industries through regional economic links, technological cooperation, and industrial collaboration. This conclusion further validates the spillover effect theory in spatial economics [83], offering a new perspective for spatial economic research in the context of digital trade. As a cross-regional economic force, digital trade accelerates the flow of data, technology, and supply chain connections across provinces through modern technologies, particularly big data, cloud computing, and e-commerce. This greatly facilitates closer collaboration between regions, enabling more efficient resource allocation. For example, advanced technologies and innovations from the eastern region are rapidly transmitted to the central and western regions via digital platforms, contributing to improvements in the technological level and product quality of local manufacturing industries. At the same time, the resource advantages of the central and western regions, such as labor and land costs, can be efficiently connected to the market demands and industrial chains of the eastern region through digital platforms, generating complementary effects that further strengthen the overall competitiveness of the manufacturing industry. From a policy perspective, the spatial spillover effects of digital trade provide valuable insights for the coordinated regional development of China's manufacturing industry. To fully leverage this effect, regional cooperation and policy support should be strengthened to facilitate the cross-regional flow and integration of digital technologies, innovation resources, and market demands. Given the current imbalance in regional development in China, particular emphasis should be placed on promoting coordinated development between the central and western regions

and the eastern region while enhancing technological and industrial collaboration between these regions. Thus, the spatial spillover effect of digital trade revealed in this study not only enriches the theoretical framework of spatial economics but also provides crucial insights for the regional coordinated development of China's manufacturing industry.

In summary, this study demonstrates that digital trade, as an emerging economic force, is gradually reshaping the competitive landscape of China's manufacturing industry. Its role in promoting manufacturing competitiveness is reflected not only in the optimization of traditional trade channels but also through new pathways such as information technology and cross-border e-commerce platforms, which lower global market entry barriers and enhance overall industrial competitiveness. Therefore, to further enhance the international competitiveness of manufacturing, it is crucial to accurately grasp the evolving trends of digital trade and clearly understand the impact and pathways of various factors on manufacturing trade conditions while fully utilizing digital trade as a driving force for the digital transformation and upgrading of the manufacturing industry.

Although this study provides important empirical evidence for the relationship between digital trade and the international competitiveness of the manufacturing industry, several limitations remain that require further exploration and improvement. First, external shocks, such as changes in international trade policies and pandemics (e.g., COVID-19), may have an impact on the role of digital trade. Specifically, during the pandemic, factors such as global supply chain disruptions and shifts in consumer behavior might have altered the operation of digital trade, thereby affecting the international competitiveness of the manufacturing industry. While this study excluded certain exceptional years (e.g., 2020–2022), the long-term effects of external shocks still warrant further investigation. This would ensure the model's identifiability and the reliability of parameter estimates. Furthermore, other potential influencing factors may also influence our conclusions. Although this study primarily focuses on the role of digital trade, factors such as national industrial policies, enterprise-level adoption of digital technologies, and the degree of market competition may affect the research outcomes to varying extents. In addition, although we have made every effort to ensure the rationality and robustness of the model, limitations still exist, such as the relatively short time span of the data and the lack of micro-level enterprise data coverage. Future research could explore these issues in greater depth to provide a more comprehensive explanation.

Future research can further explore several topics: First, the mechanisms by which digital trade impacts manufacturing industries may differ between countries and regions at varying levels of development. Therefore, cross-national comparative studies will help validate the conclusions of this study and explore similarities and differences in the development models of digital trade in different countries and regions. In particular, there may be significant differences in the driving factors, technological applications, and impacts on manufacturing competitiveness between developed and developing countries. By comparing the experiences of different nations, a more comprehensive understanding of the global impact of digital trade can be achieved. Second, the deep integration of digital trade with global supply chains, especially in the context of smart manufacturing and big data applications, warrants further exploration. Under the influence of smart manufacturing and big data, the division of labor and cooperation models in global industrial chains will undergo profound changes. How to measure the specific impact of these changes on the manufacturing competitiveness of various countries will become an important topic for future research. Lastly, the institutional development of digital trade and global cooperation mechanisms is another key area of focus. As digital trade becomes more globalized, building a more open, fair, and inclusive digital trade ecosystem has become an urgent issue for the international community. Researching how to establish more

effective global digital trade rules and cooperation mechanisms—such as promoting cross-border data flow, protecting intellectual property, and ensuring cybersecurity—will provide important insights for the development of the global digital economy. By delving into these areas, we can better understand the development trends of digital trade and its impact on the international competitiveness of manufacturing, providing policymakers with more forward-looking and practical guidance.

7. Conclusions

This study employs benchmark regression models, mediation effect models, and spatial econometric models to empirically analyze the impact of digital trade on the international competitiveness of the manufacturing industry, yielding the following conclusions: ① Digital trade significantly enhances the international competitiveness of the manufacturing industry. ② In the eastern, central, and western regions, digital trade exerts a significant positive effect on the international competitiveness of manufacturing, with the greatest impact observed in the eastern region and the smallest in the western region. ③ Digital trade indirectly enhances the international competitiveness of the manufacturing industry by attracting foreign direct investment and improving research and development capabilities. ④ The development of digital trade in a region not only boosts the international competitiveness of its manufacturing industry but also generates significant spatial spillover effects, benefiting the manufacturing competitiveness of neighboring regions.

Based on the above conclusions, this paper puts forward the following recommendations:

First, accelerating the development of digital trade is crucial to fully leverage its role in enhancing the international competitiveness of manufacturing industries. The following tailored strategies should be formulated based on the characteristics of different industries to fully exploit the empowering effects of digital trade. ① Promoting the construction of digital platforms in manufacturing and encouraging the standardized growth of digital trade to achieve the goal of digital trade-driven transformation in manufacturing. The high-end equipment manufacturing industry is a key component of China's manufacturing industry, and efforts should be made to accelerate the construction of intelligent manufacturing platforms, utilizing digital technologies to improve production efficiency and product quality. The consumer goods manufacturing industry, being highly responsive to market demand fluctuations, should promote the use of intelligent warehousing, cloud platform services, and big data analytics to help enterprises optimize production scheduling, enhance supply chain efficiency, and provide personalized product customization services. The digital transformation of the textile and garment industry is particularly critical; it is recommended to push for the establishment of digital design and production platforms to enhance supply chain transparency and reduce production waste. The automotive manufacturing industry should focus on strengthening platforms for intelligent manufacturing, digital design, and automation to enhance global competitiveness. ② Exploring the commercialization of data flow and data elements while ensuring data security. High-end equipment manufacturing involves numerous core technologies and proprietary data, requiring the establishment of data protection mechanisms, particularly in cross-border data flow, to ensure the security of sensitive data and promote the monetization of data. The consumer goods manufacturing industry should integrate consumer and production data to offer personalized services while strictly protecting data privacy. The textile and garment industry should leverage big data platforms to integrate industry data and assist enterprises in making informed decisions. The automotive industry should utilize big data to improve intelligent capabilities while ensuring the privacy of vehicle owners and the security of autonomous driving data. ③ Taking the lead in rule-making and seizing the initiative. Before digital trade rules are fully established, China should take advantage of the opportunity to propose data linkage, source code protection, and

free cross-border data flow rules that align with national conditions. The high-end equipment manufacturing industry, which involves a large number of technologically advanced and high-value-added products, faces data linkage and source code protection as key factors constraining the internationalization of enterprises. It is recommended that China advocate for the protection of source code and the establishment of digital rules for technological intellectual property in global digital trade agreements, thereby creating a favorable internationally competitive environment for domestic high-end equipment manufacturing enterprises. China should also actively advocate for the formulation of global rules governing data flow and cross-border e-commerce, ensuring smooth access for Chinese manufacturing products to international markets, while proposing data privacy protection and consumer rights protection rules that are consistent with China's national conditions on international platforms.

Second, enterprises should optimize the whole chain of “attracting, cultivating, employing, and retaining” to unleash the digital talent dividend. Differentiated strategies should be developed based on the specific conditions of Eastern, Central, and Western China to optimize the allocation of talent resources in each region: ① Rationally allocate and establish international talent management institutions to strengthen the introduction of high-level digital trade talents. The eastern region, with its developed economy, advanced digital infrastructure, and international environment, should focus on attracting top global talents in digital trade. By leveraging policies such as those in Free Trade Zones, a flexible and efficient talent introduction mechanism should be established. The central region, with weaker infrastructure, can attract external funding and technical support to establish international talent management institutions aligned with local industries, thereby driving economic transformation. The western region can leverage national policy support to develop the digital trade industry in collaboration, focusing on talent recruitment to drive infrastructure development and the digital transformation of agriculture. ② Promote collaboration among schools, government, and enterprises to establish digital trade majors and industry-focused colleges while strengthening the integration of industry, academia, and research to cultivate digital trade professionals. The eastern region, relying on universities and research institutions, can establish more digital trade-related academic programs and build a talent pool. The central region, leveraging its local industrial foundation, should focus on talent development driven by digital transformation, emphasizing disciplines such as digital economy and digital trade. This can be achieved by encouraging universities to collaborate with local industries to promote talent cultivation and technological innovation. The western region should utilize national support for education to implement an “order-based” training model, developing talents that align with local digital transformation needs, especially in fields like agricultural digitalization. ③ Foster talent that can integrate digital trade with manufacturing and strengthen talent team development. In the eastern region, where manufacturing is highly developed, there is significant potential for integrating digital trade with manufacturing. The focus should be on utilizing high-level talents who can bridge the gap between digital technology and manufacturing, thereby promoting intelligent manufacturing and digital transformation. In the central region, collaboration with enterprises should be encouraged to apply talents who can drive the intelligent and digital upgrading of traditional manufacturing industries. In the western region, the focus should be on cultivating and applying talents specialized in fields such as agricultural digitalization. ④ Improve talent incentive mechanisms to enhance the welfare of innovative talents and retain more outstanding professionals. In the eastern region, competitive salaries and favorable policies should be used to attract top global talent, particularly in the digital trade sector. The central region may offer subsidies for talent introduction and benefits, such as household registration incentives, to attract mid- to high-level digital trade professionals. Moreover, the region should strengthen local talent care and incentives by

providing career advancement and training opportunities. In the western region, national policy support can be leveraged to provide housing, living subsidies, and other incentives to optimize the working and living environment, thereby increasing the retention of talents.

Third, enterprises can accelerate the construction of new infrastructure and increase the penetration of digital trade in various industries and regions of China's manufacturing industry: ① Narrow the digital divide by promoting interconnection of information infrastructure and services across central and western regions to facilitate coordinated regional development. The eastern region, with its well-developed digital infrastructure, should prioritize enhancing the intelligence and efficiency of existing facilities, such as upgrading 5G, fiber-optic networks, and data centers. The central region can leverage public finance and market-driven approaches to establish cross-regional network platforms, promote information interconnectivity, and drive industrial digital transformation. The western region, with relatively underdeveloped infrastructure, can benefit from national policy cooperation to focus on developing digital infrastructure for traditional industries, such as transportation, energy, and agriculture. This would promote internet penetration, reduce the digital divide between the eastern and western regions, and foster the growth of cross-border e-commerce and digital agriculture. ② Improve the overall level of digital infrastructure by advancing next-generation network technologies such as 6G and optical networks, alongside new initiatives like optical cable expansion and digital microwave systems. The eastern region, with its strong technological capabilities, can serve as a pilot for the research and development of 6G and next-generation network technologies, facilitating the application of 5G and 6G technologies to upgrade high-end manufacturing, digital finance, and intelligent transportation. The central region should focus on expanding optical cables and digital microwave projects to improve network infrastructure in rural areas and small to medium-sized cities. The western region, still in the early stages of development, can accelerate infrastructure construction by collaborating with the eastern region and international partners. Optical cable expansion and digital microwave technologies can extend services to rural and remote areas, offering technological support to local agricultural, tourism, and other niche industries, thereby promoting the growth of the digital economy. ③ Actively engage in overseas digital infrastructure construction, ensure information security, and improve the convenience of international communications and the efficiency of cross-border data flows. Manufacturing enterprises can drive the development of digital infrastructure in overseas markets through international expansion, especially in areas such as production equipment, logistics management, and supply chain digitalization. The eastern region, with its robust economic foundation, can serve as a key area for the development of overseas digital infrastructure. By collaborating with international enterprises through investments and partnerships, it can build digital trade infrastructure and improve the efficiency of cross-border data flow and international communication through cooperation with global network infrastructure.

Fourth, by leveraging foreign direct investment (FDI) to promote the deep integration of digital technologies with China's manufacturing industry, enterprises can enhance the quality and effectiveness of foreign capital: ① Promoting the digital transformation of the manufacturing industry through foreign direct investment and facilitating the development of digital platforms, smart workshops, and factories. The high-end equipment manufacturing industry has stringent technological requirements, and foreign investment can introduce internationally leading automation production lines, robotic systems, and intelligent management platforms based on cloud computing and big data. These technologies enable digital control throughout the entire production process, enhancing production efficiency and resource allocation capabilities, and driving the industry toward greater intelligence and automation. The automotive manufacturing industry is gradually enter-

ing the stages of digitization and intelligence. Foreign investment can provide Chinese companies with advanced production equipment and technology to build smart factories, thereby improving production efficiency and product quality. Furthermore, foreign investment can facilitate the integration of the automotive industry with technologies such as 5G, the Internet of Things, and big data, strengthening smart manufacturing capabilities and fostering independent innovation. ② Enhancing the quality and effectiveness of foreign investment through digital trade, shifting foreign capital from quantity to quality, optimizing the structure of foreign investment, and promoting the transformation and upgrading of the manufacturing industry. Digital trade promotes global data circulation, information sharing, and technology transfer, creating new opportunities for optimizing the structure of foreign investment. First, digital trade platforms can attract foreign capital to high-value-added technology sectors, such as artificial intelligence, 5G, IoT, robotics, and semiconductors, driving the manufacturing industry toward higher technological intensity and a more advanced industrial chain. Second, digital platforms can optimize the direction of foreign investment by facilitating precise matching and information sharing, guiding foreign capital into the fields of intelligent manufacturing and digital transformation and thus enhancing the quality and effectiveness of foreign investment. Finally, by leveraging digital trade, foreign capital can more easily access and invest in China's strategic emerging industries, such as biomedicine, new energy, and smart hardware, thus optimizing investment structures and improving industrial competitiveness.

Fifth, accelerating digital technology innovation can enhance the technological support for the integration of digital trade and manufacturing industry. ① At the industry level, it is essential to build a technology-driven digital trade chain and promote the deep integration of digital technologies with various industries. For example, in the high-end equipment manufacturing industry, artificial intelligence, 5G, and the Internet of Things can be employed to enhance the automation and adaptability of intelligent manufacturing systems, thereby overcoming the bottlenecks of traditional production processes. In traditional industries such as textiles and apparel and automotive manufacturing, digital technologies can be utilized for production line optimization, supply chain coordination, and personalized customization, facilitating the transformation of these sectors toward greater intelligence and efficiency. ② At the regional level, the pace of digital technology innovation can be accelerated through coordinated regional development. For coastal areas, particularly the Yangtze River Delta and Pearl River Delta regions, priority should be given to the development of advanced manufacturing and digital technology innovation centers. Through government guidance and enterprise-driven efforts, the transformation and application of digital technology achievements can be expedited. For the central and western regions, optimizing industrial layouts and increasing policy support can promote the application of intelligent and green manufacturing technologies, advancing traditional manufacturing to higher technological levels while improving digital infrastructure and industrial competitiveness in these regions. ③ The collaborative innovation mechanism among the government, research institutions, and industry should be strengthened to consolidate the efforts of all parties. For instance, in the Beijing–Tianjin–Hebei region, collaboration between the government, research institutes, and enterprises should be enhanced, particularly in fields such as new energy and intelligent equipment, to overcome challenges in digital technology. In the central and western regions, the government can guide the establishment of technological innovation platforms and encourage joint research and development between local universities, enterprises, and foreign-invested companies, thus promoting technological innovation and industrial upgrading. Through the organic combination of industry, regional, and multi-party cooperation, digital technology can bet-

ter integrate with China's manufacturing industry, achieving technological breakthroughs and industrial upgrades.

Sixth, it is essential to establish a regional innovation collaboration system. A national strategy should be developed to optimize the regional distribution of the manufacturing industry, adopt differentiated development strategies for each region, integrate regional resources effectively, and promote coordinated development across regions. The eastern region should continue to drive digitalization by embedding digital technologies across all aspects of the existing manufacturing value chain and building a high-end intelligent manufacturing system. Simultaneously, it should reduce barriers to cross-border data flows, establish a cross-regional digital trade platform, and leverage the leading role of digital trade in advancing the high-quality development of the manufacturing industry. The central and western regions should implement policies supporting industry, talent, and investment; enhance digital infrastructure; and attract high-level talent to foster an environment conducive to the integrated development of manufacturing and digital trade. These regions should also actively join the cross-regional digital trade platform established by the eastern region and capitalize on the spatial spillover effects of the eastern region's development to accelerate the high-quality growth of manufacturing in central and western China. Additionally, local governments should identify specific challenges in the development of digital trade in the manufacturing industry based on regional characteristics and establish local science and technology innovation centers to coordinate the digital transformation of industries within their regions. Moreover, they should continue to promote the construction of a collaborative innovation system at the regional level, providing the technical support necessary for China's manufacturing industry to overcome digital transformation barriers. In the future, provincial and municipal governments should proactively plan and implement policies that will elevate the international competitiveness of China's manufacturing industry and steadily drive it toward becoming a global manufacturing power.

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References

1. Liu, W.; He, F. Construction of an indicator system for high-quality development of the Chinese economy and an international comparative study. *Explor. Econ. Issues* **2023**, *9*, 15–33. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAWpEpHq8YYbH5gYrV033sdiCHVRr264PSF9ewKIUX-JkyLxIS4LoTcZwaxL8DufE6uzMXIWtdeyy6n02WnEixfQIcwb4Xu9TxnjXRPfa8qFIYsqyAkKa1OVhAjYuWaL5uSMC5p5ljKobVuaw55r_kBUf4irddTF0rydl3q-e9edbQwip21yJt_&uniplatform=NZKPT (accessed on 15 November 2024).
2. Liu, H. Economic effects and promotion strategies for developing digital trade. *Reform* **2020**, *3*, 40–52. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAWcvgIGcHUI0kw_KYjyP-VGji9-fiFVw7Tp85Zi9anBj4R9CG4Kfj75DIKtBi-gJBDHUVo74o5aZhbz5utC5OnIp0AJQdNny-zEoKBdPrJTpTWBDCzdXpDZQHqHuQpeUBEaVU-Fyn4nvKBi7dnThCBsZ4B9czSMWmlzzGZwoQqNy1uTVxQ_FYSGqM&uniplatform=NZKPT (accessed on 15 November 2024).

3. Weber, R.H. Digital Trade in WTO-Law-Taking Stock and Looking ahead. *SSRN Electron. J.* **2010**, *5*, 1–24. Available online: <https://heinonline.org/HOL/LandingPage?handle=hein.journals/aihlp5&div=4&id=&page=> (accessed on 15 November 2024). [CrossRef]
4. Xiong, L.; Liu, H.; Liu, H. *Digital and Commerce*; Shanghai Academy of Social Sciences Press: Shanghai, China, 2011; pp. 3–5.
5. United States International Trade Commission. *Digital Trade in the U.S. and Global Economies, Part 1*; USITC Publication: Washington, DC, USA, 2013; Volume 4415, pp. 332–531. Available online: <https://www.usitc.gov/publications/332/pub4415.pdf> (accessed on 16 November 2024).
6. United States International Trade Commission. *Digital Trade in the U.S. and Global Economies, Part 2*; USITC Publication: Washington, DC, USA, 2014; Volume 4485, pp. 332–540. Available online: <https://www.usitc.gov/publications/332/pub4485.pdf> (accessed on 16 November 2024).
7. United States International Trade Commission. *Global Digital Trade: Market Opportunities and Foreign Trade Restrictions-Part 1*; United States International Trade Commission: Washington, DC, USA, 2017. Available online: <https://www.usitc.gov/publications/332/pub4716.pdf> (accessed on 17 November 2024).
8. OECD, WTO & IMF. *Handbook on Measuring Digital Trade*; OECD, WTO & IMF: Paris, France, 2019; Available online: [https://one.oecd.org/document/SDD/CSSP/WPTGS\(2019\)4/en/pdf](https://one.oecd.org/document/SDD/CSSP/WPTGS(2019)4/en/pdf) (accessed on 17 November 2024).
9. China Academy of Information and Communications Technology. *White Paper on the Development and Impact of Digital Trade*; Academy of Information and Communications Technology: Beijing, China, 2020; p. 12. Available online: <http://www.caict.ac.cn/kxyj/qwfb/bps/202012/P020201216506475945126.pdf> (accessed on 17 November 2024).
10. Ciuriak, D.; Ptashkina, M. The Digital Transformation and the Transformation of International Trade. RTA Exchange. 2018. Available online: <https://www.zbw.eu/econis-archiv/bitstream/11159/1651/1/the-digital-transformation-and-trade-ciuriak-and-ptashkina.pdf> (accessed on 17 November 2024).
11. Sheng, B.; Gao, J. Beyond traditional trade: The connotation, characteristics, and impact of digital trade. *Foreign Soc. Sci.* **2020**, *4*, 18–32. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAVofNtgr6AgICpZAuv7piYMVUHwoekZQDSn5EIMTE80Jdzh9wPmbMWoxy4Y6BRxnPQRPUStnN9yqO-HTSMhufkYI5meEai2OuoHef6d-M0fHO11Xc2wEeqPer7OAop0gQ2mkLQiEJ0iMQsiUeWv_hdilm2llJ1YKxcbASzP5VOWkvcNcd3rR&uniplatform=NZKPT (accessed on 20 November 2024).
12. López González, J.; Ferencz, J. *Digital Trade and Market Openness*, OECD Trade Policy Papers, No.217; OECD Publishing: Paris, France, 2018; p. 10. Available online: https://read.oecd-ilibrary.org/content/dam/oecd/en/publications/reports/2018/10/digital-trade-and-market-openness_60f04c17/1bd89c9a-en.pdf (accessed on 20 November 2024).
13. Xiong, L.; Ma, S. From traditional to digital trade costs: Connotation, characteristics, and impact. *J. Shanghai Univ. Commer.* **2021**, *22*, 3–13. Available online: <https://link.oversea.cnki.net/doi/10.19941/j.cnki.CN31-1957/F.2021.05.001> (accessed on 4 January 2025).
14. Melitz, M. The Impact of Trade on Intraindustry Reallocations and Aggregate Industry Productivity. *Econometrica* **2003**, *71*, 1695–1725. Available online: <https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-0262.00467> (accessed on 20 November 2024). [CrossRef]
15. Xia, J. The Origin, International Experience and Development Strategy of Digital Trade. *J. Beijing Technol. Bus. Univ. (Soc. Sci. Ed.)* **2018**, *33*, 1–10. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAUSeiVdimw3zl-oEiVur4JYBFp2RHkW04qG_9wpKdMg2C6-AizMd5aswgAvxrHPgUzuiPqcvAdq5ccYet_5XCcmjXBB3eZuxmHZ1qwjdg0YLN1dwb7O-Uhf3hcj1jGSFjd_P1TPnPL8-otaxXMYDJW1UaFMr6J-00ju6geNKQCR7igCPle-Sh&uniplatform=NZKPT (accessed on 1 December 2024).
16. Sun, J. From digital economy to digital trade: Connotation, characteristics, rules and impact. *Int. Trade Econ. Explor.* **2020**, *36*, 87–98. Available online: <https://link.oversea.cnki.net/doi/10.13687/j.cnki.gjjmts.2020.05.006> (accessed on 1 December 2024).
17. Wu, Q.; Bi, M.; Siddiqui, F.; Tang, Y. Assessing the Impact of Digital Trade on Enterprise Competitiveness: Evidence from Chinese A-Share Listed Companies. *J. Ind. Compet. Trade* **2023**, *23*, 329–362. [CrossRef]
18. Grimm, A.N. Trends in U. S. Trade in Information and Communications Technology (ICT) Services and in ICT-enabled Services. *Surv. Curr. Bus.* **2016**, *96*, 1–19. Available online: https://apps.bea.gov/scb/pdf/2016/05%20May/0516_trends_%20in_us_trade_in_ict_services2.pdf (accessed on 1 December 2024).
19. Jia, H.; Gao, X.; Xu, X.; Fang, Y. A preliminary study on the conceptual framework, index system, and measurement methods of digital trade measurement. *Stat. Res.* **2021**, *38*, 30–41. Available online: <http://www.qdatis.com/files/20220903/8c7400587372d35440525075e91bbe8.pdf> (accessed on 1 December 2024).
20. Ma, S.; Liu, J.; He, G. Digital trade power: Conceptual understanding, index construction, and potential judgment. *Int. Bus. Res.* **2022**, *13*, 1–13. Available online: <http://www.qdatis.com/files/20240218/8bd4878196fa72e37a9ff67d173772ac.pdf> (accessed on 1 December 2024).
21. Feng, Z.; Duan, D. Evaluation of the Digital Trade Development Index and Analysis of Influencing Factors: Based on Panel Data from 49 Countries. *J. Beijing Univ. Technol. (Soc. Sci. Ed.)* **2022**, *22*, 100–117. Available online: <https://journal.bjut.edu.cn/bjgydxxbskb/cn/article/pdf/preview/10.12120/bjutsxb202204100.pdf> (accessed on 2 December 2024).

22. Ye, L.; Xue, X. Digital trade promotes the high-quality development of the manufacturing industry: Effect measurement and practical path. *Econ. Syst. Reform* **2024**, *2*, 121–129. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAViRhGZx0eMw3i17oJDWcLfIBqW_Q3TAh-6MUIbobDfh4BAnhtVxJOAWs5dnFea6BOO-0eX2Wzh-aZmmKyutUwyNOvxs1gja_vecb1ZcwT4KyCX1MVrwX7KkY6445o3wCdG2YekTD4nqEsgyAeU2eaDB_a-8Lgn1DBdMMKQ138tFFLsMVHCRY0&uniplatform=NZKPT (accessed on 2 December 2024).
23. Porter, M. *The Competitive Advantage of Nations*; Free Press: New York, NY, USA, 1990; p. 855.
24. Olczyk, M.; Kordalska, A. International competitiveness of Czech manufacturing—a sectoral approach with error correction model. *Prague Econ. Pap.* **2017**, *2017*, 213–226. [CrossRef]
25. Rusu, V.D.; Roman, A. Entrepreneurial motivations in the European Union countries: An empirical approach. *Manag. Dyn. Knowl. Econ.* **2018**, *6*, 9–31. Available online: <https://www.cceol.com/search/article-detail?id=636337> (accessed on 2 December 2024).
26. Jin, B.; Li, G.; Chen, Z. Analysis of the current situation and countermeasures for improving the international competitiveness of China's manufacturing industry. *Financ. Trade Econ.* **2007**, *3*, 3–10+128. Available online: <https://link.oversea.cnki.net/doi/10.19795/j.cnki.cn11-1166/f.2007.03.001> (accessed on 2 December 2024).
27. Tang, H.; Zhang, X.; Wu, Y.; He, Z. Research on China's manufacturing industry's development quality and international competitiveness. *China Soft Sci.* **2019**, *2*, 128–142. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAWcjcD_gd7pI6TWT2Pohv8aZIRyHFVqITNEWqNF6vAUyiMo1qdFPjMogpyu1sgulOpHedd1pgFN019xohy58lSwwGQkRziJGJntVaa4mwROAhW_a0GIHAUCGqyphLjRbXyJb3Th8gZF_t52rP2DZsIbfbX-Ze4vTqUhNbbcg5dX2phBaEzDw&uniplatform=NZKPT (accessed on 5 December 2024).
28. Yu, M.; Fan, A. Empirical analysis of China's manufacturing industry international competitiveness: A comprehensive evaluation based on principal component analysis. *Guangdong Soc. Sci.* **2014**, *6*, 24–32. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAWZOyHs0DGNcU5uqY8g7dXTxfVbvxt4FIJwhWJfJQzJaQQXnOUbyqZnwFrGgrHLutYHFPmDsEZvRqHmRo38e1DJYywHwiTBz9GnmuinBgb939IuH8Ma4BmFIDRnR1WV9C3BI8w_3RBwFtFcplFWqnoWetW-NGT-kVIBV_Nwe29wb_iD_0dgH&uniplatform=NZKPT (accessed on 5 December 2024).
29. Dou, Z.; Wu, B.; Sun, Y.; Wang, T. The competitiveness of manufacturing and its driving factors: A case study of g20 participating countries. *Sustainability* **2021**, *13*, 1143. [CrossRef]
30. Frishammar, J.; Hörte, S.Å. Managing external information in manufacturing firms: The impact on innovation performance. *J. Prod. Innov. Manag.* **2005**, *22*, 251–266. [CrossRef]
31. Fan, L.; Hao, A.; Wu, Y. FDI quality characteristics and breakthrough innovation of high-tech manufacturing enterprises. *Int. Trade Econ. Explor.* **2024**, *40*, 72–89. Available online: <https://link.oversea.cnki.net/doi/10.13687/j.cnki.gjjmts.20240705.001> (accessed on 4 January 2025).
32. Yu, C.; Tang, D.; Tenkorang, A.P.; Bethel, B.J. The impact of the opening of producer services on the international competitiveness of the manufacturing industry. *Sustainability* **2021**, *13*, 11224. [CrossRef]
33. Lee, Z.; Chu, M.; Chen, S.; Tsai, C. Identifying comprehensive key criteria of sustainable development for traditional manufacturing in Taiwan. *Sustainability* **2018**, *10*, 3275. [CrossRef]
34. He, Y.; Zeng, Y. The impact of open independent innovation on the international competitiveness of industries: Based on panel data from China's manufacturing industry from 2000 to 2010. *Sci. Sci. Manag. Sci. Technol.* **2013**, *34*, 13–22. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAWw1q0izm6U_zt4VFXadoHgXA551dK9zCVS4eqzKTZo-6y3u2mg2KNbBLmvG8E4fnYyGNQ3346yyt2O0VTRnLsBqaVls9upwEZLabKvj8T36jkWS3sUWhnp4UolhFCDdLU-gO9z84pg6Hi-wz7tmWknoaVuX9Or9Y9xJW2TCNxfdxJlf2nBVnw&uniplatform=NZKPT (accessed on 5 December 2024).
35. Liu, L.; Wang, X. The relationship between innovation paths, technology intensity and international competitiveness in the manufacturing industry: An empirical study based on 17 industries. *China Sci. Technol. Forum* **2020**, *10*, 114–121+141. Available online: <https://link.oversea.cnki.net/doi/10.13580/j.cnki.fstc.2020.10.019> (accessed on 4 January 2025).
36. Cheng, X.; Yang, B. The spatial effect of China's free trade zones and improving international competitiveness in the manufacturing industry: An analysis based on spatial econometric models. *Int. Trade Issues* **2021**, *10*, 54–72. Available online: <https://link.oversea.cnki.net/doi/10.13510/j.cnki.jit.2021.10.004> (accessed on 4 January 2025).
37. Liu, L.; Guan, Q. A comparison of the international competitiveness of the manufacturing industries of China, Japan, and South Korea: A perspective based on domestic technological content. *Mod. Jpn. Econ.* **2019**, *5*, 55–69. Available online: <https://link.oversea.cnki.net/doi/10.16123/j.cnki.issn.1000-355x.2019.05.006> (accessed on 4 January 2025).
38. Yu, Z.; Tian, L. Factor endowments, industrial environment, and the development quality of China's manufacturing industry. *Res. Manag.* **2020**, *41*, 103–111. Available online: <https://link.oversea.cnki.net/doi/10.19571/j.cnki.1000-2995.2020.12.009> (accessed on 4 January 2025).
39. Pei, C.; Liu, B.; Yang, Z. Comprehensive competitive and cooperative advantages: A theoretical explanation for the enduring international competitiveness of China's manufacturing industry. *Financ. Trade Econ.* **2021**, *42*, 14–30. Available online: <https://link.oversea.cnki.net/doi/10.19795/j.cnki.cn111166/f.20210506.010> (accessed on 4 January 2025).

40. Li, A.; Li, S.; Yin, X. Technological innovation, digital investment, and the international competitiveness of China's manufacturing industry. *J. Beijing Technol. Bus. Univ. (Soc. Sci. Ed.)* **2023**, *38*, 60–72. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAV_LBwbT-y9KVJWx0Q9DgDP5lcfcbtRu2ZInVJCuKrCEmSIDvFxCOc8cwck7ZDQpR74DeoPsCJZS959i6nr9FdbMmFpNeKevswOA8DQoK6BzAQJ2pfBtpmteUa39XaKPJMM460MPyKwWO-Khv-C3PBPGeHSIf0NEaCnBLLHY5_qIqMlgi0NoVH&uniplatform=NZKPT (accessed on 5 December 2024).
41. Carlsson, R.; Otto, A.; Hall, J.W. The role of infrastructure in macroeconomic growth theories. *Civ. Eng. Environ. Syst.* **2013**, *30*, 263–273. [CrossRef]
42. Zhuang, L.; Zhou, Q.; Zhao, T. Who will lead the 'Internet Plus' of China's manufacturing industry? *Ind. Rev.* **2015**, *6*, 5–14. Available online: <https://link.oversea.cnki.net/doi/10.14007/j.cnki.cjpl.2015.04.001> (accessed on 4 January 2025).
43. Li, J.; Zhou, M. Can the Internet enhance the complexity of a country's manufacturing exports? *Int. Trade Econ. Explor.* **2017**, *33*, 24–38. Available online: <https://link.oversea.cnki.net/doi/10.13687/j.cnki.gjjmts.2017.04.003> (accessed on 4 January 2025).
44. Guo, R.; Yuan, Y.; Zhang, Y. Internet development, technological innovation and international competitiveness of manufacturing industry: An empirical analysis based on cross-country data. *Explor. Econ. Probl.* **2021**, *1*, 171–180. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAXEz9sbp9MbQEJw2NDM6z8yOBmymcCQix4Vp8sKDW7wBbIGlJtC0QUi4AUahdqV8wBaVAYzMEIDKLfISnb_q884eqIVrOVINsUBQbE1MWXUJdS3H0whmhWH-AhU2S5ctF3vN_Ai1aQUy5V94_4RewRdeYxuw1lGvVO-dsgo2b3oeKK8ssthmBl&uniplatform=NZKPT (accessed on 8 December 2024).
45. Yin, Z.H.; Choi, C.H. The effects of China's cross-border e-commerce on its exports: A comparative analysis of goods and services trade. *Electron. Commer. Res.* **2023**, *23*, 443–474. [CrossRef]
46. Szalavetz, A. Digital transformation—enabling factory economy actors' entrepreneurial integration in global value chains? *Post-Communist Econ.* **2020**, *32*, 771–792. [CrossRef]
47. Tu, Y.; Shangguan, J.Z. Cross-border E-commerce: A new driver of global trade. *Emerg. Issues Glob. Mark.* **2018**, *3*, 93–117. [CrossRef]
48. Khan, A.A.; Laghari, A.A.; Li, P.; Dootio, M.A.; Karim, S. The collaborative role of blockchain, artificial intelligence, and industrial internet of things in digitalization of small and medium-size enterprises. *Sci. Rep.* **2023**, *13*, 1656. [CrossRef]
49. Mourtzis, D.; Panopoulos, N. Digital Transformation Process Towards Resilient Production Systems and Networks. *Supply Netw. Dyn. Control.* **2022**, *10*, 11–42.
50. Stachová, K.; Stacho, Z.; Cagánová, D.; Starecek, A. Use of digital technologies for intensifying knowledge sharing. *Appl. Sci.* **2020**, *10*, 4281. Available online: <https://www.mdpi.com/2076-3417/10/12/4281> (accessed on 4 January 2025). [CrossRef]
51. Añón Higón, D.; Bonvin, D. Digitalization and trade participation of SMEs. *Small Bus. Econ.* **2024**, *62*, 857–877. [CrossRef]
52. Rietveld, J.; Nieborg, D.; Ploog, J.N. Platform Ecosystem Evolution: Implications for Complementors [C]//Academy of Management Proceedings. Briarcliff Manor, NY 10510. *Acad. Manag.* **2019**, *2019*, 11669. Available online: <https://journals.aom.org/doi/abs/10.5465/AMBPP.2019.11669abstract> (accessed on 4 January 2025).
53. Svahn, F.; Mathiassen, L.; Lindgren, R. Embracing digital innovation in incumbent firms: How Volvo cars managed competing concerns. *MIS Q.* **2017**, *41*, 239–253. Available online: <https://www.jstor.org/stable/26629645> (accessed on 4 January 2025). [CrossRef]
54. Lobo, S.; Whyte, J. Aligning and reconciling: Building project capabilities for digital delivery. *Res. Policy* **2017**, *46*, 93–107. Available online: <https://www.sciencedirect.com/science/article/pii/S0048733316301688> (accessed on 20 December 2024). [CrossRef]
55. Bohnsack, R.; Kurtz, H.; Hanelt, A. Re-examining path dependence in the digital age: The evolution of connected car business models. *Res. Policy* **2021**, *50*, 104328. Available online: <https://www.sciencedirect.com/science/article/pii/S0048733321001281> (accessed on 20 December 2024). [CrossRef]
56. Krugman, P. *The Age of Diminishing Expectations: US Economic Policy in the 1990s*; MIT Press: Cambridge, MA, USA, 1994; Available online: <https://mitpress.mit.edu/9780262611343/the-age-of-diminishedexpectations/> (accessed on 20 December 2024).
57. Prüfer, J.; Schottmüller, C. Competing with big data. *J. Ind. Econ.* **2021**, *69*, 967–1008. [CrossRef]
58. Fan, H.; Li, Y.A.; Xu, S.; Yeaple, S.R. Quality, variable markups, and welfare: A quantitative general equilibrium analysis of export prices. *J. Int. Econ.* **2020**, *125*, 103327. [CrossRef]
59. Feenstra, R.C.; Romalis, J. International prices and endogenous quality. *Q. J. Econ.* **2014**, *129*, 477–527. [CrossRef]
60. Mayer, T.; Melitz, M.J.; Ottaviano, G.I.P. Market size, competition, and the product mix of exporters. *Am. Econ. Rev.* **2014**, *104*, 495–536. [CrossRef]
61. Xie, K.; Xia, Z.; Xiao, J. The mechanism by which big data becomes a real productive factor for enterprises: A product innovation perspective. *China Ind. Econ.* **2020**, *5*, 42–60. Available online: <https://link.oversea.cnki.net/doi/10.19581/j.cnki.ciejournal.2020.05.014> (accessed on 4 January 2025).
62. Tang, Y.; Wang, Y.; Tang, C. Digital economy, market structure, and innovation performance. *China Ind. Econ.* **2022**, *10*, 62–80. Available online: <https://link.oversea.cnki.net/doi/10.19581/j.cnki.ciejournal.2022.10.004> (accessed on 4 January 2025).

63. Chen, J.; Huang, S.; Liu, Y. From empowerment to enablement—Enterprise operation management in the digital environment. *Manag. World* **2020**, *36*, 117–128+222. Available online: <https://link.cnki.net/doi/10.19744/j.cnki.11-1235/f.2020.0025> (accessed on 4 January 2025).
64. Lendle, A.; Olarreaga, M.; Schropp, S.; Vézina, P.-L. There goes gravity: eBay and the death of distance. *Econ. J.* **2016**, *126*, 406–441. [CrossRef]
65. Cai, G.; Yang, H. Can foreign direct investment improve factor market distortions in China? *China Ind. Econ.* **2019**, *10*, 42–60. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAUjQ-JoRjfxahj6xJHQ2fxLmnYhpc508UkonF8ncko3z1rnOScSwxyjYwYaiJ8XiQ70fvVxtGU9xLRmRDEp3U4d_aUsxiliPKgMaSr37xIa-Obf67APOM-TpG8VPi0ViUuTS1A7gvpOjCEqWjA_UIH78KOlPbfivuttXFRY_KBmCSfQWpKRrzL&uniplatform=NZKPT (accessed on 25 December 2024).
66. Gong, Y.; Xiao, Y.; Xiao, W. The impact of digital trade on attracting foreign direct investment. *Price Mon.* **2023**, *8*, 57–62. Available online: <https://link.oversea.cnki.net/doi/10.14076/j.issn.1006-2025.2023.08.08> (accessed on 4 January 2025).
67. Xue, D. Research on the classification system and standards of digital talent for intelligent manufacturing: Insights from the digital talent framework of the US DMDII. *Jiangsu High. Educ.* **2021**, *3*, 68–75. Available online: <https://link.oversea.cnki.net/doi/10.13236/j.cnki.jshe.2021.03.010> (accessed on 4 January 2025).
68. Cohen, W.M.; Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [CrossRef]
69. Stacks, D.W.; Salwen, M.B. (Eds.) *An Integrated Approach to Communication Theory and Research*, 2nd ed.; Routledge: London, UK, 2008. [CrossRef]
70. Acemoglu, D.; Restrepo, P. Automation and new tasks: How technology displaces and reinstates labor. *J. Econ. Perspect.* **2019**, *33*, 3–30. Available online: <https://www.aeaweb.org/article?id=10.1257/jep.33.2.3> (accessed on 25 December 2024). [CrossRef]
71. Shen, G.; Yuan, Z. Internetisation, innovation protection, and improving the quality of Chinese enterprises' export products. *World Econ.* **2020**, *43*, 127–151. Available online: <https://link.oversea.cnki.net/doi/10.19985/j.cnki.cassjwe.2020.11.007> (accessed on 4 January 2025).
72. Chen, Y.; Li, F.; Qian, Y. The role of transnational technology mergers and acquisitions in promoting the digital upgrading of manufacturing enterprises: A case study based on the perspective of the new smile curve of the value chain. *Mod. Manag. Sci.* **2024**, *1*, 139–147. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAX8x16HskbA5INf3cWcLGTKciHpCyy_rwkLFM15OYOULe6CcMgaEG_oBxgkIarvzn0_OHfqHoqmT5LGALUZNZpi0MUIBfXs7zWBwA_k_a2VLzxX0HoK7TKfoPefkccfSUsD4_IzRPJhy93l-K04okmLLfCiQ-LnGj2YM5nXxywoIGoolx-1ur&uniplatform=NZKPT (accessed on 25 December 2024).
73. Yao, Z. The impact of human capital and collaborative agglomeration on the technological complexity of exports: Based on the perspective of moderated mediating effects. *J. Xi'an Jiaotong Univ. (Soc. Sci. Ed.)* **2020**, *40*, 80–90. Available online: <https://link.oversea.cnki.net/doi/10.15896/j.xjtusxb.202004009> (accessed on 4 January 2025).
74. Ji, P.; Yuan, L. The spatial-temporal evolution characteristics and economic effects of Beijing-Tianjin-Hebei's digital product manufacturing industry. *Econ. Geogr.* **2024**, *44*, 33–42. Available online: <https://link.oversea.cnki.net/doi/10.15957/j.cnki.jjdl.2024.04.004> (accessed on 4 January 2025).
75. Yao, Z. Digital trade, industrial structure upgrading and export technology complexity: Multiple mediation effects based on structural equation models. *Reform* **2021**, *1*, 50–64. Available online: <https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAUzA-7SexQYGCAHfE7zWojLIZuCDIr9pv8cDFOo9ZTKGNxovm2rpZrhpKzZMsUCrgIQznX7rd2o5f7VGfWFcyB1HKRhmCQDBd761qBOuDKv4bxRYJwwsY1w6AEI3Y9IjgbpdBMx7jaYrTZ261vMOApYj-AcqxncsXPVNENQUY564e8PWHvUIHV&uniplatform=NZKPT> (accessed on 25 December 2024).
76. Huang, L.; Wang, Y.; Wu, Z. High-quality development of manufacturing industry and digital trade: An examination from provincial panel data from 2012 to 2020. *Mod. Manag. Sci.* **2023**, *4*, 136–145. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAW11IT6T6G6bsTJauB3wakr-W6bbNjG5C6AaB3Ao-uy2CpHouQB0b9PHPH90IOxO-Stkzjb4ChLNDXvNyqrW-rKtnNhid3Ajkl-BXLdIkIdwTSRhNaoPSfF75j9Hg6NQXxUL5JMhdO7FfQ2heZvp-Tq5nI0_lwOy_FoOAYa-0rZYkWueEsSg4q&uniplatform=NZKPT (accessed on 4 January 2025).
77. Jiang, T. Mediating and moderating effects in empirical research on causal inference. *China Ind. Econ.* **2022**, *5*, 100–120. Available online: <https://link.oversea.cnki.net/doi/10.19581/j.cnki.ciejour> (accessed on 4 January 2025).
78. Zhu, Z.; Yuan, Y.; Jiao, J. Industrial automation and manufacturing innovation behavior. *China Ind. Econ.* **2022**, *7*, 84–102. Available online: <https://link.oversea.cnki.net/doi/10.19581/j.cnki.ciejournal.2022.07.019> (accessed on 4 January 2025).
79. Dell, M. The persistent effects of Peru's mining mita. *Econometrica* **2010**, *78*, 1863–1903. [CrossRef]
80. Zhu, J.; Guo, K. The impact of digital trade on China's high-quality full employment. *Technol. Econ.* **2024**, *43*, 10–21. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAX5ETfYIaStGcozrTc9vhWNI_WSZBdnZP-YSD55aeTI790zBI5vZCj1qQ9HTBu9fwT2QDHTK-emPV7iYVZzrc9C2ynNIfrCX_NnSAZqS9bidNgWipOkQx2asg6kgI3xrV1pXgUN2AawK-bMZMmSUV1Fp_KzprLDkSFvOA2b5MwglRknmGIA7A&uniplatform=NZKPT (accessed on 4 January 2025).

81. Huang, Q.; Yu, Y.; Zhang, S. Internet development and manufacturing productivity improvement: Internal mechanism and China's experience. *China Ind. Econ.* **2019**, *8*, 5–23. Available online: <https://link.oversea.cnki.net/doi/10.19581/j.cnki.ciejournal.2019.08.001> (accessed on 4 January 2025).
82. Xiong, Y.; Hu, J. Research on the Changing Trend and Influencing Factors of the Terms of International Trade in Emerging Industries—A Comparison Based on High-end and Traditional Equipment Manufacturing Industries. *J. Nanjing Audit. Univ.* **2017**, *14*, 11–21. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAVDII9W6yJxRburpQpWvWCII9xBLfGIIaLyufVbNoObAzRvp8BKdf7cew_P0MgX_1oES0Q_eEINc-38FVNA2R9yUZ4Z30neCanY74XTgdyCtM-0GQSiR3YkkjmYKiGPaUbc4NEvipQvxHsQKNS2UBMoqALyn7-VYX5K1f6uGEosz_FYYY5UgIrS&uniplatform=NZKPT (accessed on 4 January 2025).
83. Yan, D.; Wang, Y.; Sun, W.; Li, P. A Comparative Study on the Driving Factors and Spatial Spillover Effects of Regional Economic Growth. *Geogr. Res.* **2021**, *40*, 3137–3153. Available online: https://kns.cnki.net/kcms2/article/abstract?v=tOz5m-jLbAUvxOFwEZbtRfEYyYGYcxUHCY9JAKdl1nYOD8ZHjZJfYzqvpU70Ig6rHHP9e3UaiqSqJNMky23oc0Cm9B4SRVILKPJCRetKzsah4Peh7pZubUFIGO_V34FR4KLu32jIEZdij91M-AWdCvZhD6lo226tgKNMUtyBgFtCiL0Xu0KvD3HtZ-v9MpF39&uniplatform=NZKPT (accessed on 4 January 2025).

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