# How Artificial Intelligence Innovation Reshapes China's Production Network and Trade Structure

– An Analysis Based on the Innovation Flow Table

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**Abstract**

Artificial Intelligence (AI) is reshaping the structure of economic systems with unprecedented depth. However, existing research mostly adopts a macro perspective focusing on technological innovation or input-output relationships, failing to link technology with the production-use relationships of intermediate goods. This makes it difficult to reveal AI's structural impact on the intermediate goods market. To address this, based on Chinese patent data and input-output tables, this paper measures the direct input-output linkages between industries for AI technological innovation and non-AI technological innovation, defining them as innovation flow tables. It further establishes an intermediate goods-augmented technological progress model that distinguishes between AI innovation and non-AI innovation, elucidating the impact of AI innovation on the intermediate goods market and trade networks. Empirical findings reveal that AI innovation possesses scale expansion effects, cost-saving effects, and structural upgrading effects, profoundly altering the structure of China's production network. In intermediate goods trade, it exhibits upward absorption, downward substitution, and export expansion effects. Furthermore, this paper identifies the mechanism through which AI innovation disseminates its influence by promoting non-AI innovation. It also finds that core AI algorithm and software innovation play a primary role, with the secondary industry serving as the main channel for these effects. Finally, this paper provides new empirical evidence and policy insights for AI-driven industrial transformation.

**Keywords:** Artificial Intelligence; Innovation Flow Table; Production Network; Intermediate Goods Trade; Intermediate Goods-Augmented Technological Progress

## 1 Introduction

Artificial Intelligence (AI), as a strategic technology leading a new round of technological revolution and industrial transformation, is integrating into human production and daily life with unprecedented breadth and depth. Currently, AI technology is accelerating its iterative evolution, triggering profound changes across various fields and industries in the economy and society. How to better leverage AI's enabling role has become a critical question for advancing the construction of a modern industrial system and cultivating new quality productive forces. Driven by the synergistic forces of algorithmic optimization, enhanced computing power, and data accumulation, AI demonstrates powerful versatility and penetrative ability, promoting quality and efficiency improvements in traditional industries while also spawning a multitude of new business forms and models. Intelligent robots entering factories and homes are gradually becoming a trend, with various intelligent agents playing important roles in production and daily life. Clearly, AI has profoundly changed human lifestyles and the structure of global production networks.

How does AI innovation reshape traditional production networks? Existing research suggests that AI can promote technological innovation, drive industrial upgrading, reduce trade costs, optimize resource allocation, and alter international comparative advantages, thereby changing production networks and trade structures. However, existing studies lack a joint perspective that combines technological innovation with the input-output relationships of intermediate goods to study the role of AI innovation. The fundamental reason is the difficulty of decomposing technological innovation into inter-industry flow relationships that align with the input-output structure of intermediate goods. To achieve this challenging leap, this paper uses patent data as a proxy for technological innovation. To match technologies with industries, this paper utilizes probabilities for various industries to produce various patent types provided by the Max Planck Institute for Innovation and Competition, and probabilities for various patent types to be used by various industries as studied by Travis J. Lybbert and Nikolas J. Zolas. It establishes an inter-industry innovation flow probability matrix for different patent types. Then, by combining data from the China Patent Database and the "Strategic Emerging Industry Classification and International Patent Classification Reference Relationship Table (2021) (Trial)" issued by the Office of the China National Intellectual Property Administration in 2021, it identifies the production and usage of AI innovation across different industries, thereby linking the respective production-use relationships of technology and intermediate goods.

To analyze how AI technological innovation affects the intermediate goods market, this paper reconstructs an intermediate goods-augmented technological progress model. By distinguishing between AI and non-AI technological innovations, it analyzes how increased AI technological innovation acts upon the intermediate goods production network and import-export trade. Furthermore, integrating the World Input-Output Tables published by the Asian Development Bank from 2007 to 2021 and constructing panel models, it finds that AI innovation generates a significant boosting effect on the demand for domestic intermediate goods, deepening the domestic economic cycle. Simultaneously, it significantly increases the import of intermediate goods from developed countries while reducing imports from developing countries, and promotes the export of high-value intermediate goods imbued with AI empowerment to the global market (including developed countries), reflecting the roles of upward absorption, downward substitution, and export expansion along the value chain. Additionally, the application of AI technology reduces sectoral direct input coefficients, enhancing production efficiency. Finally, this paper finds that the use of AI technology promotes an industry's position in the global value chain.

The main contributions of this paper include: Based on Chinese patent data and input-output tables, it constructs an inter-industry innovation flow probability matrix for different technology types, measuring China's AI technology and non-AI technology innovation flow tables. It establishes an intermediate goods-augmented technological progress model distinguishing between AI innovation and non-AI innovation, discovering that AI innovation possesses structural upgrading, scale expansion, and cost-saving effects. It identifies the role of AI technological innovation on the domestic production network and intermediate goods trade structure. Through mechanism analysis and employing matrix regression methods, it finds that AI innovation disseminates its influence by enabling non-AI innovation. Further consistency analysis reveals that AI innovation profoundly changes China's production network structure, deepening the domestic economic cycle, and exhibits upward absorption, downward substitution, and export expansion effects in intermediate goods trade. It finds that core AI algorithm and software innovation are the main engines generating these effects, with the secondary industry serving as the primary channel.

The remainder of this paper is organized as follows: Section 2 reviews relevant research literature and identifies current research gaps; Section 3 constructs the intermediate goods-augmented technological progress model incorporating AI technology and non-AI technology subject to AI innovation spillovers, and proposes hypotheses; Section 4 presents the research design, introducing the econometric model and variable definitions; Section 5 details the data, elaborating on the process of constructing the innovation flow table and introducing the sources and processing of other required data; Section 6 reports baseline regression results, robustness and endogeneity tests, and heterogeneity analysis; Section 7 reports mechanism effects and heterogeneity analysis; The final section presents the conclusions and policy implications.

# 2 Literature Review

## 2.1 Technology-Industry Concordance

To accurately map patented technologies, which serve as proxies for innovation, onto specific industrial activities, Schmookler (1966) pioneered the assignment of "sectors of use" to U.S. patent classes (USPC), marking the first attempt to establish an empirical link between technology and industry. Pavitt (1984) emphasized that technological change exhibits significant sector-specific patterns, providing a theoretical basis for analyzing technological innovation from an industry perspective. Building on this, Patel and Pavitt (1991) established an empirical mapping between technology and the industry of origin at the firm level for the first time by analyzing the patent portfolios of large corporations. In the "OECD Technology Concordance" report, Johnson (2002) systematically elaborated on an extension method based on the Yale Technology Concordance (YTC). The core advantage of the YTC lies in its probabilistic framework: it utilizes historical data from the Canadian Patent Office, which, between 1978 and 1993, assigned both technology classifications (IPC) and industry classifications (Canadian SIC) to patents simultaneously. This allows for the calculation of the joint probability that an IPC patent belongs to a specific manufacturing sector and a specific sector of use (Kortum & Putnam, 1997). This method has been widely adopted by subsequent researchers. For example, Mann and Puttmann (2023), in their study on automation patents, directly applied the empirical frequencies of IPC-SIC relationships based on the YTC framework, calculated and provided by Silverman (2002), to probabilistically match U.S. patents to the industries where they were likely used. Johnson's (2002) work aligned this framework with the International Standard Industrial Classification (ISIC), generating the OECD Technology Concordance table. Yu Lili et al. (2025) measured the direct inter-industry input-output linkages for all types of technological innovation in China over six consecutive years based on the YTC.

However, the early methods represented by the YTC have significant limitations that constrain their application. Lybbert and Zolas (2014) pointed out that the YTC relies entirely on patent data from a specific period (1978-1993) and a specific country (Canada), embedding unavoidable temporal, spatial, and technological biases. Mann and Puttmann (2023) also acknowledge that assigning patents to industries and regions through probabilistic matching introduces imprecision. To overcome these limitations, Lybbert and Zolas (2014) proposed an innovative "algorithmic links with probabilities" approach. This method departs from the reliance on manually coded data, instead employing data mining and probabilistic algorithms to extract information directly from vast amounts of patent text. Dorner and Harhoff (2018) proposed a novel technology-industry concordance table based on "inventor-establishment linked data." This method precisely matches patent inventor data from the European Patent Office (EPO) with employee employment records in the German social security system, obtaining the industry classification information (NACE code) of the establishment where the inventor was employed at the time of patent filing. This provides precise information on the "industry of origin" of the technology, reflecting the true micro-environment in which technological innovation occurs. This paper is precisely based on these latest research findings to measure the innovation flow table.

## 2.2 The Impact of AI Innovation on Intermediate Goods Production Networks and Trade Structure

Research on the impact of AI innovation on intermediate goods networks reveals significant dual effects. On one hand, AI drives demand for high-tech intermediate goods, promoting supply chain stability. Liu Bin and Pan Tong (2020) point out that AI boosts demand for high-value-added intermediate inputs by reducing trade costs, promoting technological innovation, and optimizing resource allocation. Lyu Yue et al. (2020), using micro-level data, further confirm that AI enhances firms' degree of embeddedness in the global value chain by improving total factor productivity and reducing production costs. Regarding supply chain stabilization, Xu Heng et al. (2024) suggest that AI helps mitigate the risk of supply chain "disruption." Tao Feng et al. (2023) find that as intra-product specialization deepens, firms' reliance on intermediate inputs deepens, while information asymmetry and the "bullwhip effect" within supply chains can easily lead to supply-demand fluctuations. Liu Wenge et al. (2024) also point out that AI, through intelligent processing of historical and real-time data, can more accurately predict intermediate goods demand, assist firms in optimizing import strategies, and enhance supply chain stability and responsiveness. On the other hand, AI, through automation and task substitution, suppresses demand for some traditional labor-intensive intermediate goods. Acemoglu and Restrepo's (2020) model of robot-worker competition shows that the use of industrial robots leads to declines in employment and wages, indirectly reflecting reduced demand for labor-intensive intermediate links in the production process. Li Lei et al. (2021) further indicate that the employment-suppressing effect of industrial robots is mainly concentrated in traditional labor-intensive industries and low-skilled labor groups, further confirming the structural characteristic that AI might compress demand for certain intermediate goods.

Overall, the impact of AI on intermediate goods demand exhibits a coexistence of structural substitution and structural expansion (Acemoglu & Restrepo, 2019). Although existing research reveals the dual impact of AI on intermediate goods demand from different perspectives, most remains at the level of theoretical mechanism discussion or macro-level inference, lacking empirical tests based on data from the "producing industry $\times$ using industry" dimension that connects AI technological innovation with intermediate goods.

# 3 Model Construction

## 3.1 Theoretical Model Framework

To analyze how AI innovation affects the demand for intermediate goods, this paper builds upon the intermediate goods-augmented technological progress model constructed by Wu Han and Guo Kaiming (2025), distinguishing between AI technological progress and non-AI technological progress that incorporates the spillover effects of AI innovation. It is assumed that the total output function of each industry conforms to the Cobb-Douglas form, and that each industry is produced by a representative firm. Factor prices and the market prices of products and intermediate goods are exogenously given. The total output of industry $i$ is given by:

$$Q_i = A_i \left(K_i^{\alpha_i} L_i^{1-\alpha_i}\right)^{\varphi_i} M_i^{1-\varphi_i} \tag{1}$$

where, $A_i$ is the total factor productivity measured by total output (separate from intermediate goods-augmented technological progress and not the focus of the model), $\alpha_i$ is the output elasticity of capital in value added, $\varphi_i$ is the output elasticity of value added in total output, $K_i$ is the capital goods consumed in the production of industry $i$, $L_i$ is the labor consumed in the production of industry $i$, and $M_i$ is the composite intermediate good, with unit cost $p_i$. The price of capital goods is $r_i$, and the price of labor is $\omega_i$.

Furthermore, the intermediate good $M_{ij}$ provided by industry $j$ to industry $i$ is decomposed into an AI sub-intermediate good $M_{ij}^{AI}$ and a non-AI sub-intermediate good $M_{ij}^{nonAI}$, forming a two-layer structure of "sub-intermediate good $\rightarrow$ industry intermediate good $\rightarrow$ total composite intermediate good." The production function for the AI sub-intermediate good $M_{ij}^{AI}$ conforms to the Cobb-Douglas form.

$$M_{ij}^{AI} = A_{ij}^{AI} \bullet \left[\left(K_{ij}^{AI}\right)^{\alpha_{ij}^{AI}} \left(L_{ij}^{AI}\right)^{1-\alpha_{ij}^{AI}}\right]^{\varphi_{ij}^{AI}} \bullet \left(m_{ij}^{AI}\right)^{1-\varphi_{ij}^{AI}} \tag{2}$$

where, $K_{ij}^{AI}$, $L_{ij}^{AI}$ are the capital and labor inputs for producing $M_{ij}^{AI}$, $\alpha_{ij}^{AI}$ is the output elasticity of capital, $\varphi_{ij}^{AI}$ is the elasticity of value added in the production of the intermediate good, and $m_{ij}^{AI}$ is the intermediate good consumed by industry $j$ to produce $M_{ij}^{AI}$ for industry $i$, with price $P_j$. $A_{ij}^{AI}$ is the productivity of the AI sub-intermediate good.

Similarly, the production function for the non-AI sub-intermediate good $M_{ij}^{nonAI}$ is:

$$M_{ij}^{nonAI} = A_{ij}^{nonAI} \bullet \left[\left(K_{ij}^{nonAI}\right)^{\alpha_{ij}^{nonAI}} \left(L_{ij}^{nonAI}\right)^{1-\alpha_{ij}^{nonAI}}\right]^{\varphi_{ij}^{nonAI}} \bullet \left(m_{ij}^{nonAI}\right)^{1-\varphi_{ij}^{nonAI}} \tag{3}$$

where, $K_{ij}^{nonAI}$, $L_{ij}^{nonAI}$ are the capital and labor inputs for producing $M_{ij}^{nonAI}$, $\alpha_{ij}^{nonAI}$ is the output elasticity of capital, $\varphi_{ij}^{nonAI}$ is the elasticity of value added in the production of the intermediate good, and $m_{ij}^{nonAI}$ is the intermediate good consumed by industry $j$ to produce $M_{ij}^{nonAI}$ for industry $i$, also with price $P_j$. Similarly, $A_{ij}^{nonAI}$ is the productivity of the non-AI sub-intermediate good.

Let $\theta_{ij}^{AI}$ be the relative productivity technology parameter of the AI sub-intermediate good within the intermediate good provided by industry $j$ to industry $i$:

$$\theta_{ij}^{AI} = \frac{A_{ij}^{AI}}{\sum_k \left(A_{ik}^{AI} + A_{ik}^{nonAI}\right)} \tag{4}$$

$\theta_{ij}^{nonAI}$ is the relative productivity technology parameter of the non-AI sub-intermediate good within the intermediate good provided by industry $j$ to industry $i$:

$$\theta_{ij}^{nonAI} = \frac{A_{ij}^{nonAI}}{\sum_k \left(A_{ik}^{AI} + A_{ik}^{nonAI}\right)} \tag{5}$$

Therefore, $\theta_{ij}$ is the relative productivity technology parameter of the intermediate good provided by industry $j$ to industry $i$:

$$\theta_{ij} = \theta_{ij}^{AI} + \theta_{ij}^{nonAI} \tag{6}$$

The production of both AI and non-AI sub-intermediate goods provided by industry $j$ to industry $i$ relies on traditional factors. They are aggregated into the composite intermediate good provided by industry $j$ to industry $i$, with the aggregation function specified in CES form:

$$M_{ij} = \left[ \left(\frac{\theta_{ij}^{AI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{AI}\right)^{\frac{\sigma-1}{\sigma}} + \left(\frac{\theta_{ij}^{nonAI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{nonAI}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

where, $\theta_{ij}^{AI}$, $\theta_{ij}^{nonAI}$ are the weights of AI and non-AI sub-intermediate goods in $M_{ij}$, directly corresponding to the strength of the two types of intermediate goods-augmenting technologies (a higher weight indicates a stronger enabling effect of the technology on intermediate goods production). $\sigma$ is the elasticity of substitution between AI and non-AI sub-intermediate goods; when $\sigma = 1$, it degenerates to the CD form.

Each type of composite intermediate good used by industry $i$ is again aggregated via a CES function into the total composite intermediate good $M_i$ used by industry $i$:

$$M_i = \left[ \sum_j \theta_{ij}^{\frac{1}{\varepsilon_i^M}} \bullet M_{ij}^{\frac{\left(\varepsilon_i^M - 1\right)}{\varepsilon_i^M}} \right]^{\frac{\varepsilon_i^M}{\left(\varepsilon_i^M - 1\right)}} \tag{8}$$

where, $\varepsilon_i^M > 0$ is the elasticity of substitution among intermediate goods from different industries in the intermediate input of industry $i$.

## 3.2 Theoretical Analysis

The total cost of industry $i$ is composed of the factor costs of total output $(r_i K_i + \omega_i L_i + p_i M_i)$ and the intermediate good costs $(\sum_j P_{ij} M_{ij})$, where $P_{ij}$ is the unit cost of the intermediate good $M_{ij}$ provided by industry $j$ to industry $i$. To derive $P_{ij}$, its sub-cost must first be derived through cost minimization of the sub-intermediate goods.

For the AI sub-intermediate good cost $P_{ij}^{AI}$, the objective function is to minimize the production cost of $M_{ij}^{AI}$: $\min TC_{ij}^{AI} = r_i K_{ij}^{AI} + \omega_i L_{ij}^{AI} + P_j m_{ij}^{AI}$, yielding the AI sub-intermediate good cost:

$$P_{ij}^{AI} = \frac{1}{A_{ij}^{AI}} \bullet \left[ \frac{\left(\frac{r_j}{\alpha_{ij}^{AI}}\right)^{\alpha_{ij}^{AI}} \left(\frac{\omega_j}{1-\alpha_{ij}^{AI}}\right)^{1-\alpha_{ij}^{AI}}}{\varphi_{ij}^{AI}} \right]^{\varphi_{ij}^{AI}} \bullet \left(\frac{P_j}{1-\varphi_{ij}^{AI}}\right)^{1-\varphi_{ij}^{AI}} \tag{9}$$

This equation reflects the logic of intermediate good pricing, with the cost advantage of AI technology embodied solely through $A_{ij}^{AI}$; an increase in $A_{ij}^{AI}$ leads to a decrease in $P_{ij}^{AI}$.

For the non-AI sub-intermediate good cost $P_{ij}^{nonAI}$, similarly, the objective function is $\min TC_{ij}^{nonAI} = r_i K_{ij}^{nonAI} + \omega_i L_{ij}^{nonAI} + P_j m_{ij}^{nonAI}$, yielding the non-AI sub-intermediate good cost:

$$P_{ij}^{nonAI} = \frac{1}{A_{ij}^{nonAI}} \bullet \left[ \frac{\left(\frac{r_j}{\alpha_{ij}^{nonAI}}\right)^{\alpha_{ij}^{nonAI}} \left(\frac{\omega_j}{1-\alpha_{ij}^{nonAI}}\right)^{1-\alpha_{ij}^{nonAI}}}{\varphi_{ij}^{nonAI}} \right]^{\varphi_{ij}^{nonAI}} \bullet \left(\frac{P_j}{1-\varphi_{ij}^{nonAI}}\right)^{1-\varphi_{ij}^{nonAI}} \tag{10}$$

From the cost minimization of $M_{ij} = \left[ \left(\frac{\theta_{ij}^{AI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{AI}\right)^{\frac{\sigma-1}{\sigma}} + \left(\frac{\theta_{ij}^{nonAI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{nonAI}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$, i.e., $\min TC_{ij} = P_{ij}^{AI} M_{ij}^{AI} + P_{ij}^{nonAI} M_{ij}^{nonAI}$, we obtain:

$$\frac{P_{ij}^{AI}}{P_{ij}^{nonAI}} = \frac{\left(\frac{\theta_{ij}^{AI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{AI}\right)^{\frac{-1}{\sigma}}}{\left(\frac{\theta_{ij}^{nonAI}}{\theta_{ij}}\right)^{\frac{1}{\sigma}} \left(M_{ij}^{nonAI}\right)^{\frac{-1}{\sigma}}} = \left(\frac{\theta_{ij}^{AI}}{\theta_{ij}^{nonAI}}\right)^{\frac{1}{\sigma}} \left(\frac{M_{ij}^{AI}}{M_{ij}^{nonAI}}\right)^{\frac{-1}{\sigma}} \tag{11}$$

Dividing Equation (10) and Equation (11), which represent $P_{ij}^{nonAI}$ and $P_{ij}^{AI}$ respectively, yields:

$$\frac{P_{ij}^{AI}}{P_{ij}^{nonAI}} = \frac{A_{ij}^{nonAI}}{A_{ij}^{AI}} \cdot \frac{\Phi_{ij}^{AI}}{\Phi_{ij}^{nonAI}} \tag{12}$$

where $\Phi_{ij}^{AI} = \left[ \frac{\left(\frac{r_j}{\alpha_{ij}^{AI}}\right)^{\alpha_{ij}^{AI}} \left(\frac{\omega_j}{1-\alpha_{ij}^{AI}}\right)^{1-\alpha_{ij}^{AI}}}{\varphi_{ij}^{AI}} \right]^{\varphi_{ij}^{AI}} \bullet \left(\frac{p_j}{1-\varphi_{ij}^{AI}}\right)^{1-\varphi_{ij}^{AI}}$ and $\Phi_{ij}^{nonAI}$ are fixed constants.

Combining Equation (11) and Equation (12) yields the intermediate goods input ratio:

$$\frac{M_{ij}^{AI}}{M_{ij}^{nonAI}} = \frac{\theta_{ij}^{AI}}{\theta_{ij}^{nonAI}} \bullet \left(\frac{P_{ij}^{AI}}{P_{ij}^{nonAI}}\right)^{-\sigma} = \frac{\theta_{ij}^{AI}}{\theta_{ij}^{nonAI}} \bullet \left(\frac{A_{ij}^{AI}}{A_{ij}^{nonAI}}\right)^{\sigma} \cdot \left(\frac{\Phi_{ij}^{nonAI}}{\Phi_{ij}^{AI}}\right)^{\sigma} \tag{13}$$

From this, **Hypothesis 1: AI innovation has a "structural upgrading effect" on intermediate goods.** The stronger the inter-industry flow of AI innovation, the stronger the export competitiveness of intermediate goods produced by that industry, and the boosting effect is particularly pronounced for exports to developed country markets. Symmetrically, the stronger the inter-industry flow of AI innovation, the more the demand for imported intermediate goods will tilt towards high-tech intermediate goods from developed countries, correspondingly reducing reliance on low-tech intermediate goods from developing countries.

From Equation (7), the composite intermediate good cost can be derived:

$$P_{ij} = \left[ \left( \frac{\theta_{ij}^{AI}}{\theta_{ij}} \right) \left( P_{ij}^{AI} \right)^{1-\sigma} + \left( \frac{\theta_{ij}^{nonAI}}{\theta_{ij}} \right) \left( P_{ij}^{nonAI} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{14}$$

Taking the logarithmic differential:

$$d \ln P_{ij} = s_{ij}^{AI} d \ln P_{ij}^{AI} \tag{15}$$

where $s_{ij}^{AI} = \frac{P_{ij}^{AI} M_{ij}^{AI}}{P_{ij}^{AI} M_{ij}^{AI} + P_{ij}^{nonAI} M_{ij}^{nonAI}} = \frac{\theta_{ij}^{AI} \left( P_{ij}^{AI} \right)^{1-\sigma}}{P_{ij}{}^{1-\sigma}}$ is the cost share of the AI sub-intermediate good. From Equation (8), the composite intermediate good cost for industry $i$ is $P_i^M$, such that $P_i^M = p_i$:

$$P_i^M = \left[ \sum_j \theta_{ij} \bullet P_{ij}{}^{1-\varepsilon_i^M} \right]^{\frac{1}{1}-\varepsilon_i^M} \tag{16}$$

Taking the logarithmic differential:

$$d \ln P_i^M = \sum_j s_{ij}^M d \ln P_{ij} \tag{17}$$

where $s_{ij}^M = \theta_{ij} \left( \frac{P_{ij}}{P_i^M} \right)^{1-\varepsilon_i^M} = \frac{P_{ij} M_{ij}}{\sum_k P_{ik} M_{ik}}$, is the cost share of the sub-composite intermediate good $M_{ij}$ in industry $i$, measuring the importance of the sub-composite intermediate good in the total intermediate input of industry $i$.

Therefore, for industry $i$, cost minimization yields the total cost function $TC_i = c_i Q_i$, where the unit cost $c_i$ is:

$$c_i = \frac{1}{A_i} \bullet \left[ \frac{\left( \frac{r_i}{\alpha_i} \right)^{\alpha_i} \left( \frac{\omega_i}{1-\alpha_i} \right)^{1-\alpha_i}}{\varphi_i} \right]^{\varphi_i} \bullet \left( \frac{P_i^M}{1-\varphi_i} \right)^{1-\varphi_i} \tag{18}$$

From the production function, the demand for intermediate goods is:

$$M_i = (1 - \varphi_i) \cdot \frac{TC_i}{P_i^M} \tag{19}$$

Furthermore, starting from the cost minimization of industry $i$, the demand for the composite intermediate good $M_{ij}$ can be derived as:

$$M_{ij} = \theta_{ij} \left( \frac{P_{ij}}{P_i^M} \right)^{-\varepsilon_i^M} M_i \tag{20}$$

Thus, the total value of the composite intermediate good $M_{ij}$ is obtained:

$$V_{ij} = P_{ij} M_{ij} = \theta_{ij} \left( \frac{P_{ij}}{P_i^M} \right)^{1-\varepsilon_i^M} (1 - \varphi_i) \, TC_i \tag{21}$$

At the same time, the direct input coefficient can be derived, where $P_i$ is the market price of industry $i$'s output faced by the firm:

$$a_{ij} = \frac{V_{ij}}{P_i Q_i} = \theta_{ij} \left(\frac{P_{ij}}{P_i^M}\right)^{-\varepsilon_i^M} (1-\varphi_i) \frac{TC_i}{P_i} = \theta_{ij} \left(\frac{P_{ij}}{P_i^M}\right)^{1-\varepsilon_i^M} (1-\varphi_i) \frac{c_i}{P_i} \tag{22}$$

Solving for $\frac{\partial \ln V_{ij}}{\partial \ln A_{ij}^{AI}}$:

$$\frac{\partial \ln V_{ij}}{\partial \ln A_{ij}^{AI}} = \left(1-\varepsilon_i^M\right) \frac{\partial \ln\left(\frac{P_{ij}}{P_i^M}\right)}{\partial \ln A_{ij}^{AI}} + \frac{\partial \ln c_i}{\partial \ln A_{ij}^{AI}} + \frac{\partial \ln Q_i}{\partial \ln A_{ij}^{AI}} \tag{23}$$

Noting that changes in the relative productivity technology parameters are negligible, we have $\frac{\partial \ln\left(\frac{P_{ij}}{P_i^M}\right)}{\partial \ln A_{ij}^{AI}} = \frac{\partial \ln P_{ij}}{\partial \ln A_{ij}^{AI}} - \frac{\partial \ln P_i^M}{\partial \ln A_{ij}^{AI}} = -\left(1-s_{ij}^M\right) s_{ij}^{AI}$, and $\frac{\partial \ln c_i}{\partial \ln A_{ij}^{AI}} = -\left(1-\varphi_i\right) s_{ij}^M s_{ij}^{AI}$. Additionally, defining $\frac{\partial \ln Q_i}{\partial \ln c_i} = -\eta_i$, a decrease in cost increases firm profits, leading to expanded output. Assuming the supply elasticity of industry $i$ is $\eta_i > 0$, then $\frac{\partial \ln Q_i}{\partial \ln A_{ij}^{AI}} = \eta_i \left(1-\varphi_i\right) s_{ij}^M s_{ij}^{AI}$. Therefore:

$$\frac{\partial \ln V_{ij}}{\partial \ln A_{ij}^{AI}} = s_{ij}^{AI} \left[(1-\varepsilon_i^M)(s_{ij}^M - 1) + (1-\varphi_i) s_{ij}^M (\eta_i - 1)\right] \tag{24}$$

where $s_{ij}^{AI}$ is always positive. Next, solving for $\frac{\partial \ln a_{ij}}{\partial \ln A_{ij}^{AI}}$:

$$\begin{aligned}
\frac{\partial \ln a_{ij}}{\partial \ln A_{ij}^{AI}} &= \frac{\partial \ln c_i}{\partial \ln A_{ij}^{AI}} + \left(1-\varepsilon_i^M\right) \frac{\partial \ln\left(\frac{P_{ij}}{P_i^M}\right)}{\partial \ln A_{ij}^{AI}} \\
&= -\left(1-\varphi_i\right) s_{ij}^M s_{ij}^{AI} - \left(1-\varepsilon_i^M\right)\left(1-s_{ij}^M\right) s_{ij}^{AI} \\
&= s_{ij}^{AI}\left[-\left(1-\varphi_i\right) s_{ij}^M - \left(1-\varepsilon_i^M\right)\left(1-s_{ij}^M\right)\right] \\
&= s_{ij}^{AI}\left[\varepsilon_i^M - 1 - \left(\varepsilon_i^M - \varphi_i\right) s_{ij}^M\right]
\end{aligned} \tag{25}$$

Wu Han and Guo Kaiming (2025), using the World Input-Output Tables from 1995-2014, estimated $\varepsilon_i^M$ for the three industries to be 1.406, 1.356, and 0.893, respectively. Simultaneously, $\varphi_i$ is obtained by taking the mean of the ratio of nominal value added to nominal total output for the three industries. Assuming $\eta_i$ takes a relatively small value of 1.2, and taking China's 2015 input-output table as an example, calculating $(1-\varepsilon_i^M)(s_{ij}^M - 1) + (1-\varphi_i) s_{ij}^M (\eta_i - 1)$ yields results shown in Table 1. For production-use relationships accounting for over 90% of intermediate goods flows, this value is positive. For these production relationships, $\frac{\partial \ln V_{ij}}{\partial \ln A_{ij}^{AI}} > 0$. If $\eta_i$ takes a larger value, even more production relationships would yield $\frac{\partial \ln V_{ij}}{\partial \ln A_{ij}^{AI}} > 0$. Thus, **Hypothesis 2: AI innovation has a "scale expansion effect" on the demand for intermediate goods.** The stronger the inter-industry flow of AI innovation, the greater the demand for intermediate goods.

Calculating $\left[\varepsilon_i^M - 1 - \left(\varepsilon_i^M - \varphi_i\right) s_{ij}^M\right]$ yields results shown in Table 2. For production-use relationships accounting for over 80% of intermediate goods flows, this value is negative, and it is most negative for production-use relationships within the secondary industry. For these production relationships, $\frac{\partial \ln a_{ij}}{\partial \ln A_{ij}^{AI}} < 0$. Therefore, **Hypothesis 3: AI**

Table 1: Simulation Calculation of the Scale Expansion Effect

| | Primary Industry | Secondary Industry | Tertiary Industry |
|---|---|---|---|
| Primary Industry | 0.304 (1%) | 0.339 (4.8%) | -0.100 (0.4%) |
| Secondary Industry | 0.262 (1.9%) | 0.206 (57.2%) | -0.001 (8.4%) |
| Tertiary Industry | 0.380 (0.3%) | 0.320 (13.4%) | 0.047 (12.6%) |

Note: The percentages in parentheses represent the proportion of the corresponding intermediate goods flow in total intermediate goods.

**innovation has a "cost-saving effect" on the direct input coefficient.** AI innovation, by enhancing the efficiency of intermediate goods usage, reduces the intermediate input required per unit of output, lowering the direct input coefficient, reflecting AI's role in improving the efficiency of industrial resource allocation.

Table 2: Simulation Calculation of the Scale Expansion Effect

| | Primary Industry | Secondary Industry | Tertiary Industry |
|---|---|---|---|
| Primary Industry | 0.148 (1%) | 0.307 (4.8%) | -0.110 (0.4%) |
| Secondary Industry | -0.290 (1.9%) | -0.515 (57.2%) | -0.374 (8.4%) |
| Tertiary Industry | 0.284 (0.3%) | 0.157 (13.4%) | -0.492 (12.6%) |

Note: The percentages in parentheses represent the proportion of the corresponding intermediate goods flow in total intermediate goods.

# 4 Research Design

To systematically test the three hypotheses proposed in Chapter 3, this paper constructs the following econometric models.

## 4.1 Scale Expansion Effect Regression Model

To study the scale expansion effect of AI innovation on intermediate goods and the structural effect on import demand, the following baseline regression model is specified:

$$Y_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 A_{ij,t-1}^{total} + \alpha_3 A_{ij,t-1}^{dom} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{26}$$

where, $t$ represents time, and $ij$ represents the industry pair consisting of industry $i$ and industry $j$. The dependent variables include: the intermediate goods from industry $j$ consumed by industry $i$ in year $t$, used to test AI's effect on boosting total demand; the domestic intermediate goods from industry $j$ consumed by industry $i$ in year $t$, used to test AI's role in deepening the domestic economic cycle; the imported intermediate goods from industry $j$ consumed by industry $i$ in year $t$, used to test AI's effect on boosting import demand and promoting the international cycle. The core explanatory variable $AI_{ijt}$ represents the AI innovation produced by industry $j$ and used by industry $i$ in year $t$. Control variables include: the direct input coefficient $A_{ij,t-1}^{total}$, representing the intermediate goods from industry $j$ consumed per unit of total output produced by industry $i$

in year $t-1$, to control for inherent, non-AI-driven technological and economic linkages between industries; the domestic direct input coefficient $A_{ij,t-1}^{dom}$, representing the domestic intermediate goods from industry $j$ consumed per unit of total output produced by industry $i$ in year $t-1$, to further control for inherent dynamic inertia. $\delta_{ij}$ is the industry pair fixed effect for industries $i$ and $j$, used to control for all time-invariant characteristics specific to that industry pair; $\mu_t$ is the time fixed effect, used to control for common shocks from the macroeconomic cycle; $\varepsilon_{ijt}$ is the model estimation residual. This paper employs clustered standard errors, adjusting for clustering at both the inter-industry and time dimensions, and partially uses heteroskedasticity-robust standard errors to address potential intra-group correlation and heteroskedasticity issues.

## 4.2 Structural Upgrading Effect Regression Model

To study the structural upgrading effect of AI innovation, its heterogeneous effects on different types of intermediate goods, including the boosting effect on high-end intermediate goods and the substitution effect on low-end intermediate goods, the following regression model is established:

$$Y_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 A_{ij,t-1}^{total} + \alpha_3 A_{ij,t-1}^{dom} + \alpha_3 IO_{ij,t-1} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{27}$$

where the dependent variables include: intermediate goods imported by industry $i$ in year $t$ from industry $j$ in developed countries, used to test AI's promotion of Chinese industries' upward absorption; intermediate goods imported by industry $i$ in year $t$ from industry $j$ in developing countries, used to test AI's promotion of Chinese industries' downward substitution. The control variable adds $IO_{ij,t-1}$, representing the intermediate goods from industry $j$ consumed by industry $i$ in year $t-1$, while other explanatory variables remain unchanged.

To study whether the structural upgrading effect of AI innovation, by empowering product quality and cost advantages of an industry, can boost the export of that industry's products to be used more as intermediate goods, thereby achieving an elevated position in the industrial chain and upgrading in the global value chain, the following regression model is established:

$$Y_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 A_{ij,t-1}^{import} + \alpha_3 A_{ij,t-1}^{total} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{28}$$

where the dependent variables include: intermediate goods exported by Chinese industry $j$ in year $t$ and consumed by industry $i$ in other countries, used to test AI's enhancement of export competitiveness of intermediate goods; intermediate goods exported by industry $j$ in year $t$ and consumed by industry $i$ in developed countries, used to verify AI's promotion of Chinese industries embedding into high-end value chains; intermediate goods exported by industry $j$ in year $t$ and consumed by industry $i$ in developing countries, used to test AI's assistance in maintaining the advantages of low-end industries in China; the meanings of other explanatory variables remain unchanged.

## 4.3 Cost Saving Effect Regression Model

To analyze whether AI innovation can reduce the intermediate input required per unit of output, ultimately lowering the industry's direct input coefficient, the following regression model is established:

$$Y_{ijt} = \alpha_0 + \alpha_1 \log\left(AI_{ijt} + 1\right) + \alpha_2 \log\left(EXPAI_{ijt} + 1\right) + \alpha_3 A_{ij,t-1}^{dom} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{29}$$

where the dependent variables include: the direct input coefficient, representing all intermediate goods from industry $j$ consumed per unit of total output produced by industry $i$ in year $t$; the domestic direct input coefficient, representing domestic intermediate goods from industry $j$ consumed per unit of total output produced by industry $i$ in year $t$; the imported direct input coefficient, representing imported intermediate goods from industry $j$ consumed per unit of total output produced by industry $i$ in year $t$. Since the range of the dependent variables is between 0 and 1, to further alleviate heteroskedasticity, AI innovation and non-AI innovation are transformed using the natural logarithm.

Although fixed effects models and control variables can mitigate some omitted variable issues, there may still be bidirectional causality between AI innovation and intermediate goods trade. To address this, we employ strategies such as lagged explanatory variables and instrumental variable methods in the robustness and endogeneity tests.

# 5 Data Description and Measurement of the Innovation Flow Table

## 5.1 Data Sources and Processing

The main data used in this paper and their sources are as follows: 1.The probability table $P^P$ for various industries to produce various patent types, provided by the Max Planck Institute for Innovation and Competition. It contains the probabilities for 608 IPC4 standard patent categories to be produced by 86 sector categories under the NACE Rev. 2 classification. The element $p^P_{hj}$ in the table represents the proportion of patents submitted by inventors employed in industry $j$ under patent classification $h$. This probability matrix characterizes the tendency of each industry to produce certain technologies. 2. The probability table $P^U$ for various patent types to be used by various industries, studied by Travis J. Lybbert and Nikolas J. Zolas based on the PATSTAT database provided by the European Patent Office (EPO). The PATSTAT database contains patent data from 86 countries since 1990, including detailed information on over 100 million patent applications. This probability table contains the probabilities for 636 IPC4 standard patent categories to be used by 83 sector categories under ISIC Rev. 4. The element $p^U_{hj}$ in the table represents the proportion of patents under patent classification $h$ most likely to be used by industry $j$. This probability matrix characterizes the tendency of each industry to use certain patents. 3. Chinese patent data publicly available from the China National Intellectual Property Administration, compiled according to the publication announcement year of patents, covering all patent applications filed in mainland China from 1985 to 2023, including key fields such as patent number, IPC classification, patent type, and announcement year, totaling over 5 million items. 4. The multi-regional input-output tables (ADB-MRIO) for 2007-2021 published by the Asian Development Bank, providing domestic/imported/exported intermediate goods flow data, total output, and value-added data for 35 industries across 62 economies.

From the ADB-MRIO, China's total output data and input-output data for domestic intermediate goods, imported intermediate goods, and exported intermediate goods are selected. Based on whether the importing country and exporting country are developed countries, sums are calculated to obtain data on China's intermediate goods imports from developed and developing countries, and exports of intermediate goods to developed and developing countries for each year from 2007 to 2021. Based on China's input-output data over the years, the domestic direct input coefficient matrix, imported direct input coefficient matrix, and competitive-type direct input coefficient matrix are calculated.

## 5.2 Measurement of the Innovation Flow Table

To align with the input-output tables, this paper unifies the industry dimensions of $P^P$ and $P^U$ to the 35 ISIC Rev. 4 sectors in the ADB-MRIO based on the correspondence between ISIC and NACE industry classifications, achieving precise one-to-one, many-to-one, and one-to-many mappings. Furthermore, by matching the patent production probability table and the patent use probability table, an intersection is taken based on the 4-digit IPC codes, resulting in 596 patent categories where production probabilities and use probabilities are matched.

Table 3: Schematic Diagram of Production Probability Table and Use Probability Table for Patent Category G06F

| Production Probability for G06F | | Use Probability for G06F | |
|---|---|---|---|
| Producing Industry | Probability | Using Industry | Probability |
| Agriculture, Forestry, Animal Husbandry and Fishery | 0 | Agriculture, Forestry, Animal Husbandry and Fishery | 0 |
| ... | ... | ... | ... |
| Electrical and Optical Equipment | 0.387 | Electrical and Optical Equipment | 0.857 |
| ... | ... | ... | ... |
| Real Estate Activities | 0.4 | Real Estate Activities | 0.086 |
| ... | ... | ... | ... |
| Other Social and Personal Services | 0.002 | Other Social and Personal Services | 0.028 |

For a specific patent category $h$, its production tendency column vector in the patent production probability table $P^P$ is $p_h^P(35 \times 1)$, and its use tendency column vector in the patent use probability table $P^U$ is $p_h^U(35 \times 1)$. Combining these generates the $35 \times 35$ inter-industry innovation flow probability matrix $P_h$ for patent $h$:

$$P_h = diag\left(p_h^P\right) \bullet \left[p_h^U, p_h^U, \cdots, p_h^U\right] \tag{30}$$

where $diag\left(p_h^P\right)$ is the diagonalization of the production probability vector $p_h^P$, representing the source of technology $h$; the matrix on the right is formed by replicating the use probability vector $p_h^U$ column-wise, representing the use of technology $h$. The economic meaning of the element $p_h^{ij}$ in matrix $P_h$ is the joint probability that technology $h$ is produced by industry $j$ and used by industry $i$, and $\sum_i \sum_j p_h^{ij} = 1$.

This paper selects 27 patent categories corresponding to the "Artificial Intelligence" subcategory under the "First Generation Information Technology Industry" in the "Strategic Emerging Industry Classification and International Patent Classification Reference Relationship Table" as AI patents, serving as proxies for AI innovation; correspondingly, the other 569 patent categories are non-AI patents, serving as proxies for non-AI innovation. Chinese patent data compiled for each year is screened, deleting patents lacking an "IPC classification." The patent type and main IPC classification of each patent are identified, and statistics are compiled based on the main IPC classification to obtain the total innovation volume $patent_{ht}^{CN}$ of China in patent category $h$ over the years ($t$). Then, multiplying $patent_{ht}^{CN}$ by the inter-industry innovation flow probability matrix $P_h$ for patent category $h$ yields the innovation flow situation of this technology across various industries in China over the years.

For year $t$, the AI innovation flow table $AI_t$ is calculated as follows:

$$AI_t = \sum_{h \in H_{AI}} \left( patent_{ht}^{CN} \bullet P_h \right) \tag{31}$$

where $H_{AI}$ represents the set of AI patent categories. The calculation of the non-AI innovation flow table $NonAI_t$ is analogous, yielding data on the inter-industry production and use of AI innovation and non-AI innovation from 1985 to 2023. The measurement results show that AI technological innovation is mainly used by 11 industries.

Considering China's accession to the WTO in 2001 and the implementation of the second revision of the "Patent Law of the People's Republic of China" starting in 2001, this paper selects 2001 as the starting year for the innovation flow table. Considering the average two-year time lag from patent publication announcement to grant announcement, 2021 is selected as the end year, covering 21 years. To correspond with the input-output data, the sample starting year is set at 2007, with a total of 15 periods in the sample.

Table 4: Schematic Diagram of China's AI Innovation Flow Table for 2021

| Innovation Unit | Agriculture | ... | Electrical | ... | Real Estate | ... | Other |
|---|---|---|---|---|---|---|---|
| Agriculture | 0 | ... | 1.754 | ... | 0.449 | ... | 0.828 |
| ... | ... | | ... | | ... | | ... |
| Electrical | 0 | ... | 19803.05 | ... | 1128.453 | ... | 8299.032 |
| ... | ... | | ... | | ... | | ... |
| Real Estate... | 0 | ... | 16216.62 | ... | 1278.877 | ... | 3886.603 |
| ... | ... | | ... | | ... | | ... |
| Other... | 0 | ... | 202.783 | ... | 7.392 | ... | 116.202 |

# 6 Empirical Results and Analysis

## 6.1 Scale Expansion Effect

The results of the baseline regression (26) are shown in Table 5. AI innovation technology has a scale expansion effect on the demand for intermediate goods, generating a significant boosting effect. Decomposing this effect, the boosting effect of AI innovation on domestic intermediate goods is the main component, larger than its effect on imported intermediate goods. This is mainly because AI is most closely integrated with local services, software, data, and application scenarios; its boosting effects prioritize and concentrate on erupting within the domestic industrial chain. The rapid development of AI innovation is making China's domestic production network tighter and more complex, forming the resilient backbone of the internal circulation. China has preliminarily built an autonomous AI industrial ecosystem. At the same time, the super-large market provides ample opportunities for the implementation and iteration of AI technology. China possesses the world's largest digital economy market, offering rich scenarios for AI applications; China's complete industrial chain system also provides effective support for the autonomous development of AI technology.

Table 5: Regression Results for the Scale Expansion Effect

| | All Intermediate Goods | Domestic Intermediate Goods | Imported Intermediate Goods |
|---|---|---|---|
| AI | 11.116* | 7.723* | 3.393* |
| | (3.932) | (3.932) | (1.781) |
| Control Variables | Yes | Yes | Yes |
| $R^2$ | 0.903 | 0.895 | 0.920 |
| Adjusted $R^2$ | 0.158 | 0.151 | 0.165 |
| Time FE | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered by industry-year are in parentheses. Due to space limitations, the regression results for control variables are not reported. This applies to the following tables as well.

## 6.2 Structural Upgrading Effect

The results of the baseline regression (27), which more finely decomposes imported intermediate goods into those imported from developed countries and those from developing countries, are shown in Table 6. The regression results reveal that AI innovation changes the structure of China's imported intermediate goods—significantly increasing the import of intermediate goods from developed countries, reflecting the innovation synergy between AI and high-tech intermediate goods. The research and application of AI rely on high-end technological products from developed countries, and domestic enterprises' technological transformation also requires importing high-tech intermediate goods that are temporarily unavailable domestically. Importantly, the results indicate that AI innovation reduces the import of intermediate goods from developing countries. This finding highly aligns with existing research results, indicating that AI innovation consolidates the competitiveness and irreplaceable position of Chinese industries. Therefore, this import growth is not simply scale expansion but a technology-driven structural upgrade, reflecting China's inherent need to connect upwardly with the global technology frontier during the AI empowerment process, while downwardly maintaining competitiveness in existing industrial fields, effectively substituting for labor-intensive, low-value-added intermediate goods that previously needed to be imported in large quantities from developing countries. This achieves an autonomous and controllable cross-border layout of China's industrial chain, helping the Chinese economy to establish new drivers and production capacities first, and then gradually phase out and replace relatively backward production capacities and supply systems.

The results of the baseline regression (28) are shown in Table 7. The higher the flow of AI innovation between industry $j$ and industry $i$, the more the export of products from industry $j$ is used as demand by industry $i$ in other countries, and this increase is

Table 6: AI Structural Upgrading Effect——Results of Heterogeneity Analysis of Imported Intermediate Goods

| | Imports from Developed | Imports from Developing |
|---|---|---|
| AI | 3.743* | -0.842* |
| | (0.614) | (0.456) |
| Control Variables | Yes | Yes |
| $R^2$ | 0.883 | 0.893 |
| Adjusted $R^2$ | 0.389 | 0.076 |
| Time FE | Yes | Yes |
| Industry Pair FE | Yes | Yes |
| Clustered SE | Yes | Yes |

significant. As China's AI technology continuously innovates and deeply integrates with the real economy, AI innovation empowers the quality and cost advantages of industries' intermediate goods, boosting demand for exported intermediate goods. This boosting effect is stronger for export markets in developed countries, which are more sensitive to technology, and relatively weaker for export markets in developing countries. AI innovation exhibits the characteristic of boosting exports while simultaneously upgrading their structure.

This paper's empirical evidence shows that as Chinese industries develop AI innovation, their demand for intermediate goods from developed countries increases. However, it also increases the export competitiveness of China's own high-value intermediate goods imbued with AI empowerment, especially the competitiveness of exports to developed countries. This demonstrates that the strengthening of commercial and technological ties between China and developed countries does not lead to external dependence. As AI innovation integrates with production, the competitiveness of Chinese products exported to developing countries is also rapidly increasing, and to a certain extent, it substitutes for low-end imports from developing countries. This ensures that while China's economic sectors move up the value chain, their competitiveness at the low-end industrial level is also guaranteed.

Table 7: Structural Upgrading Effect——Results of Heterogeneity Analysis of Exported Intermediate Goods

| | Exported Goods | Exports to Developed | Exports to Developing |
|---|---|---|---|
| AI | 2.135** | 1.239** | 0.897* |
| | (0.942) | (0.525) | (0.417) |
| Control Variables | Yes | Yes | Yes |
| $R^2$ | 0.928 | 0.935 | 0.883 |
| Adjusted $R^2$ | 0.237 | 0.254 | 0.145 |
| Time FE | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |

## 6.3 Cost Saving Effect

The results of the baseline regression (29) are shown in Table 8. The coefficient of the core explanatory variable log(AI+1) is significantly negative across all models, indicating that the application of AI indeed significantly reduces the intermediate input cost per unit of output by improving production efficiency. The economy's growth is becoming less dependent on traditional material inputs. At the current stage, the application of AI in China is more closely integrated with the domestic industrial chain, and its cost-reducing and efficiency-enhancing benefits first benefit the domestic supply chain system. AI empowerment enables enterprises to use intermediate goods more precisely, creating the same or even higher value with fewer physical inputs, driving the transition from high-speed growth to high-quality development. Further observing the coefficient structure reveals that the negative impact of AI on the domestic direct input coefficient is greater than its impact on the imported direct input coefficient. This differential saving magnitude indicates that the cost-saving effect of AI is more potent within the domestic production network.

Table 8: Regression Results for the Cost-Saving Effect

| | Direct Input Coefficient | Domestic Direct Input Coefficient | Imported Direct Input Coefficient |
|---|---|---|---|
| log(AI+1) | -0.0004** | -0.0002* | -0.0002*** |
| | (0.0002) | (0.0001) | (0.00005) |
| Control Variables | Yes | Yes | Yes |
| $R^2$ | 0.989 | 0.987 | 0.951 |
| Adjusted $R^2$ | 0.324 | 0.370 | 0.044 |
| Time FE | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |

## 6.4 Robustness and Endogeneity Tests

### 6.4.1 Robustness Tests

To examine the robustness of the above conclusions, this paper conducted the following tests: 1. Expanding the time window: adjusting the sample window from 2007-2021 to 2007-2023, increasing the sample size; 2. Replacing some dependent variables: using the total input coefficient to replace the direct input coefficient in the test of the cost-saving effect; 3. Reconstructing the innovation production-use network: weighting patents according to different "patent types," assigning invention patents a weight twice that of other patent types.

Since intermediate goods are homogeneous and closely related in the tests of structural upgrading, scale expansion, and cost-saving effects, the robustness and endogeneity tests only examine three types of intermediate goods—total intermediate goods, intermediate goods imported from developing countries, and exported intermediate goods—and the direct input coefficient.

**1. Expanding the Time Window** To mitigate potential endogeneity issues such as omitted explanatory variables, the sample space is appropriately expanded by incorporating data from 2022-2023, which was not used in the previous regressions. This includes technology production-use data and intermediate goods production-use data for 2022-2023, and then re-estimating the parameters to be evaluated. The test results are shown in Table 9 and are consistent with the main regression results. The conclusions remain unchanged after incorporating recent data, indicating that the effect of AI innovation transcends economic cycles and represents a structural change.

Table 9: Robustness Test 1——Expanding the Time Window

| | All Goods | Imports from Developing | Exported Goods | Direct Input Coef. |
|---|---|---|---|---|
| AI | 12.209*** | -0.930*** | 2.57*** | |
| | (2.204) | (0.187) | (0.417) | |
| log(AI+1) | | | | -0.0004** |
| | | | | (0.0002) |
| Control Variables | Yes | Yes | Yes | Yes |
| $R^2$ | 0.900 | 0.870 | 0.902 | 0.989 |
| Adjusted $R^2$ | 0.100 | 0.136 | 0.191 | 0.420 |
| Time FE | Yes | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |

**2. Replacing Some Dependent Variables** The total input coefficient is used to replace the direct input coefficient in the regression to test the robustness of the cost-saving effect. The total input coefficient matrix $L$, with element $L_{ijt}$, represents all intermediate goods from industry $j$ completely consumed (directly and indirectly) per unit of total output produced by industry $i$ in year $t$. The results are shown in Table 10 and are consistent in sign with the main regression. The effect remains significant even after covering all indirect linkages, proving that the impact of AI innovation propagates along the depth of the industrial chain, and its network effects cannot be ignored.

Table 10: Robustness Test 2——Replacing Some Dependent Variables

| | Total Input Coef. | Domestic Total Input Coef. | Imported Total Input Coef. |
|---|---|---|---|
| log(AI+1) | -0.0008* | -0.002*** | -0.0002*** |
| | (0.0004) | (0.001) | (0.00005) |
| Control Variables | Yes | Yes | Yes |
| $R^2$ | 0.974 | 0.974 | 0.948 |
| Adjusted $R^2$ | 0.281 | 0.240 | 0.053 |
| Time FE | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |

**3. Reconstructing the Explanatory Variable** To further alleviate endogeneity and demonstrate the robustness of the results, patents are weighted according to the "patent type" field. "Invention applications" and "invention grants" are given a weight of 2, while other patent types are given a weight of 1. This better highlights the innovative significance of invention patents, elevating the analysis from a patent production-use network to a purer innovation production-use network. The regression results are shown in Table 11 and are consistent with the baseline regression results. The conclusions are strengthened after emphasizing invention patents, which precisely confirms the core logic—AI technological innovations with high substantive innovative content produce profound industrial catalytic effects. Conversely, this also proves the validity of the core variable construction in this paper.

Table 11: Robustness Test 3——Reconstructing the Explanatory Variable

| | All Goods | Imports from Developing | Exported Goods | Direct Input Coef. |
|---|---|---|---|---|
| AI | 6.289** | -0.485* | 1.212** | |
| | (3.164) | (0.262) | (0.544) | |
| log(AI+1) | | | | -0.0005** |
| | | | | (0.0002) |
| Control Variables | Yes | Yes | Yes | Yes |
| $R^2$ | 0.903 | 0.893 | 0.929 | 0.989 |
| Adjusted $R^2$ | 0.158 | 0.077 | 0.240 | 0.324 |
| Time FE | Yes | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |

The results of the above robustness tests are all consistent with the main regression model, indicating that the model results in this paper are very robust.

### 6.4.2 Endogeneity Tests

The inter-industry flow of AI innovation and changes in industries' AI patent inventions are closely related to industry characteristics, macroeconomic and social development trends, and potential inter-industry linkages. These factors also influence the production-use relationships of intermediate goods between industries and changes in cross-border intermediate goods trade. This leads to potential endogeneity issues in the series of panel models constructed in this paper. This paper uses two methods to mitigate endogeneity: 1. Lagging explanatory variables: Lagging the key explanatory variable by two periods in the fixed effects model; 2. Using U.S. AI patent data from the United States Patent and Trademark Office (USPTO) for 2007-2021 to construct a U.S. AI innovation flow table, serving as an instrumental variable for China's AI innovation flow table. Regarding relevance, as the world's leading innovative nations, the U.S. and China have numerous connections in technological progress, such as talent and knowledge. U.S. AI patents and Chinese AI patents have a natural correlation, and technological progress in one country can drive the other. Moreover, U.S. innovation flows are unlikely to be directly affected by inter-industry intermediate goods flows within China or by China's import and export of intermediate goods. They reflect inter-industry technological linkages in the U.S., satisfying the exogeneity condition.

**1. Lagging Explanatory Variables** To alleviate potential endogeneity, AI innovation and non-AI innovation are lagged by one period. The test results are shown in Table 12. Lagged AI innovation has a scale expansion effect, significantly boosting demand for all intermediate goods, promoting a decline in the use of intermediate goods imported from developing countries, and also promoting the export of intermediate goods from industries with close AI innovation flow linkages, generating a cost-saving effect. These results are consistent with the main regression. This test proves that the effect of AI innovation on the intermediate goods market is persistent, not a fleeting phenomenon, but has a cumulative effect over time.

Table 12: Endogeneity Test 1——Lagging Explanatory Variables

| | All Goods | Imports from Developing | Exported Goods | Direct Input Coef. |
|---|---|---|---|---|
| Lagged AI | 15.763* | -1.199* | 2.923** | |
| | (7.980) | (0.613) | (1.202) | |
| log(Lagged AI+1) | | | | -0.0004* |
| | | | | (0.0002) |
| Control Variables | Yes | Yes | Yes | Yes |
| $R^2$ | 0.903 | 0.893 | 0.929 | 0.989 |
| Adjusted $R^2$ | 0.161 | 0.079 | 0.247 | 0.324 |
| Time FE | Yes | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |

**2. Instrumental Variable Method** Using the U.S. AI innovation flow as an instrumental variable for China's AI innovation flow, estimation is carried out using a two-stage least squares method with heteroskedasticity-robust standard errors. The test results are shown in Table 13. All first-stage F-tests are passed, indicating that the U.S. AI innovation flow can effectively fit China's AI innovation flow. The fitted Chinese AI innovation is significant in all panel models, and the research conclusions remain consistent with the baseline regression results. The instrumental variable results suggest that the endogeneity issue is largely mitigated.

Table 13: Endogeneity Test 2——Instrumental Variable Method

| | All Goods | Imports from Developing | Exported Goods | Direct Input Coef. |
|---|---|---|---|---|
| Fitted AI | 14.641*** | -0.894* | 1.257** | |
| | (5.410) | (0.539) | (0.578) | |
| log(Fitted AI+1) | | | | -0.0004*** |
| | | | | (0.0002) |
| Control Variables | Yes | Yes | Yes | Yes |
| $R^2$ | 0.903 | 0.896 | 0.926 | 0.989 |
| Adjusted $R^2$ | 0.156 | 0.032 | 0.213 | 0.324 |
| First-stage F | Passed | Passed | Passed | Passed |
| Industry Pair FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |

# 7 Further Discussion

The preceding empirical analysis has proven that AI innovation reshapes the structure of the intermediate goods market. This chapter aims to verify its core transmission mechanisms and, from the perspective of heterogeneity analysis, present the uneven process by which AI reshapes the structure of the intermediate goods market.

## 7.1 Mechanism Effects

General-purpose technology theory suggests that AI technology possesses innovation complementarity, stimulating non-AI technological innovation. Performing a matrix regression on the AI innovation flow table and the non-AI innovation flow table from 2001-2021, selecting the optimal lag order, with the non-AI innovation matrix lagged by one period $EXPAI_{t-1}$ and the AI innovation matrix lagged by one period $AI_{t-1}$, the regression equation takes the following form:

$$EXPAI_t = A_1 \cdot EXPAI_{t-1} \cdot A_2{}' + B_1 \cdot AI_{t-1} \cdot B_2{}' + E_t \tag{32}$$

where the coefficient matrix $B_1$ is the row interaction coefficient matrix of AI innovation on non-AI innovation, i.e., the production-direction interaction coefficient matrix. Its element $b_1^{mk}$ represents how an increase in AI production in industry $k$ affects non-AI production in industry $m$. $B_2$ is the column interaction coefficient matrix of AI innovation on non-AI innovation, i.e., the use-side interaction coefficient matrix. Its element $b_2^{mk}$ represents how an increase in AI use in industry $k$ affects non-AI use in industry $m$. By distinguishing between the production direction and the use direction, one can precisely test the GPT attribute of AI—whether it stimulates other technological innovations primarily through its R&D and creation process or through its practical application process.

Using the Bootstrap method for robustness testing, at a 90% significance level, the results show that the production-direction coefficient matrix $B_1$ is statistically almost entirely insignificant. This indicates that an industry simply developing and producing more AI patents does not directly incentivize other industries or itself to produce more non-AI patents. The knowledge creation activity of AI itself has relatively limited externalities.

However, conversely, in the use direction, the effect of AI innovation on non-AI innovation is significant. Figure 1 reports the column interaction coefficient matrix $B_2$. In the figure, the column direction is AI innovation, and the row direction is non-AI innovation. It shows the impact on other industries' use of non-AI innovation when each industry uses one more unit of AI innovation. Compared to fixed effects models, the matrix regression model captures the relationships between observations and variables more meticulously, identifying the total effect including spillover effects. The regression results show that, on average, one additional unit of AI innovation can drive approximately 0.9 units of non-AI innovation.

Some of the relationships with larger positive effects include: Electrical and optical equipment on food, beverages and tobacco products; textiles and textile products; paper products, printing and publishing; Human health and social work on chemicals and chemical products; food, beverages and tobacco products; electrical and optical equipment; Other social and personal services on chemicals and chemical products; basic metals and

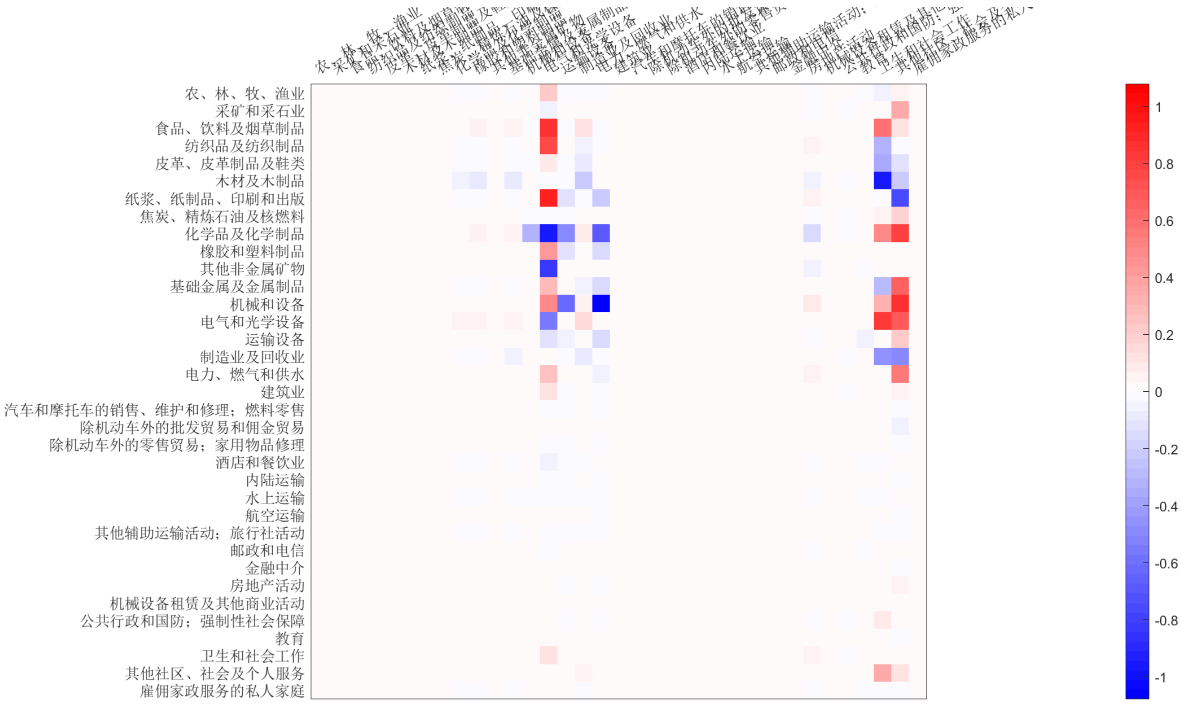


Figure 1: Figure 1 The Impact of Industry Use of AI Innovation Technology on the Use of Non-AI Innovation Technology

fabricated metal products; machinery and equipment n.e.c.; electrical and optical equipment. Some of the relationships with larger negative effects include: Electrical and optical equipment on chemicals and chemical products; other non-metallic mineral products; electrical and optical equipment itself; Transport equipment on machinery and equipment n.e.c.; Human health and social work on wood and products of wood; Other community, social and personal services on paper products, printing and publishing. Overall, the industries most positively affected are food, beverages and tobacco products; electrical and optical equipment; electricity, gas and water supply. The industries most negatively affected are wood and products of wood; chemicals and chemical products; other non-metallic mineral products; manufacturing n.e.c. and recycling.

In production reality, the implementation of AI often requires supporting process improvements, hardware upgrades, or organizational changes, thereby stimulating cross-domain technological synergy. On average, AI innovation drives nearly one unit of non-AI innovation, suggesting that AI does not simply substitute for traditional technologies but often forms a complementarity with non-AI innovation. A key question is: Is this technological catalysis indeed the actual channel through which AI affects trade structure and the value chain? To this end, we conduct a mediation effect test by constructing the following regression models:

$$IO_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 EXPAI_{ijt} + \alpha_3 Control_{ijt} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{33}$$

$$IMPORTIO_{ijt}^{developing} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 EXPAI_{ijt} + \alpha_3 Control_{ijt} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{34}$$

$$EXPORTIO_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 EXPAI_{ijt} + \alpha_3 Control_{ijt} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{35}$$

The regression results are shown in Table 14. Adding non-AI innovation to the regression model renders the effect of industry using AI innovation on the use of intermediate goods imported from developing countries insignificant. This indicates that non-AI innovation fully mediates the effect of AI innovation on the heterogeneity in the source of intermediate goods demand. In the regression for all intermediate goods, after adding non-AI innovation, the significance and magnitude of AI innovation do not change significantly, while the effect of non-AI innovation is insignificant. This suggests that non-AI innovation is not a mediating factor for AI innovation in the scale expansion effect. In the regression for exported intermediate goods, after adding non-AI innovation, both non-AI innovation and AI innovation have significant effects, and the effect of AI innovation decreases somewhat. This indicates that non-AI innovation partially mediates the effect of AI innovation on export promotion.

Table 14: Mechanism Test Results

| | All Goods | Imports from Developing | Exported Goods | GVC Position Index |
|---|---|---|---|---|
| AI | 9.407* | -0.351 | 1.267* | |
| | (4.918) | (0.257) | (0.724) | |
| log(AI+1) | | | | 0.008 |
| | | | | (0.006) |
| EXPAI | -0.028 | -0.362*** | 0.022* | |
| | (0.087) | (0.017) | (0.012) | |
| log(EXPAI+1) | | | | 0.009*** |
| | | | | (0.005) |
| Control Variables | Yes | Yes | Yes | Yes |
| $R^2$ | 0.876 | 0.908 | 0.919 | 0.443 |
| Adjusted $R^2$ | 0.173 | 0.301 | 0.249 | 0.397 |
| Time FE | Yes | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |

In the dimension of "reducing imports from developing countries," non-AI innovation plays a fully mediating role. This means that AI itself does not directly exclude low-end imports. It must do so by enabling the existing vast non-AI technology system, enhancing overall production efficiency and product quality, to achieve import substitution and value chain climbing. This proves mechanistically that the path of "AI + traditional industry integration" is far more fundamental for industrial upgrading than simply developing the AI industry itself. In promoting exports, non-AI innovation is a partial mediator. This indicates that AI's boost to exports operates through a dual channel: on one hand, AI innovation, by catalyzing non-AI innovation, enhances overall product quality and competitiveness; on the other hand, AI itself may serve as a core selling point or unique function of the product, directly attracting the international market.

The regression results reveal that in the digital era, the driving force for the transformation of industrial and supply chains is shifting from traditional factor cost advantages to a "synergistic advantage of the industrial ecosystem based on intelligent technology." China's case shows that by deepening internal networks and selectively coupling with external ones through AI, a nonlinear and networked leap in value chain status can be achieved. Finally, this mechanism test carries important policy implications: AI's upgrading effect on the industrial chain is largely achieved by activating and enhancing the traditional technology system. Simply pursuing the "production" of AI innovations without focusing on their integrated "use" with existing industries will significantly diminish their upgrading effect.

## 7.2 Heterogeneity Analysis

To delve deeper into how different types and different industries of AI innovation differentially impact the intermediate goods market, this section divides AI innovation into two major categories: core algorithm and software innovation, and application system and hardware equipment innovation. All industries are divided into the secondary industry and non-secondary industries for heterogeneity analysis.

### 7.2.1 AI Type Heterogeneity

AI core algorithm and software innovation includes machine learning, neural networks, pattern recognition, natural language processing, knowledge engineering, software simulation, etc. It encompasses the core computational models, learning methods, software frameworks, and data processing techniques of AI, representing the core technological level for realizing AI functions. AI application system and hardware equipment innovation includes medical health, automatic control, security monitoring, human-computer interaction, etc. It encompasses AI application systems in specific fields, specialized hardware equipment, control and interaction systems, belonging to the implementation and integration level of AI.

Table 15: AI Category Heterogeneity Test Results

| | All Goods | All Goods | Imports from Developing | Imports from Developing | Exported Goods | Exported Goods |
|---|---|---|---|---|---|---|
| AI Hardware | 17.415 | | -1.344* | | 3.213 | |
| | (11.683) | | (0.913) | | (1.980) | |
| AI Software | | 13.198* | | -1.002* | | 2.54* |
| | | (6.791) | | (0.536) | | (1.210) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.903 | 0.903 | 0.893 | 0.893 | 0.928 | 0.928 |
| Adjusted $R^2$ | 0.159 | 0.158 | 0.078 | 0.075 | 0.235 | 0.236 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Pair FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust SE | Yes | Yes | Yes | Yes | Yes | Yes |

Dividing all AI innovations into two categories, the regression results are shown in Table 15. AI software innovation plays a significant role in boosting demand for all intermediate goods, imported intermediate goods, and exported intermediate goods, exhibiting scale expansion, cost-saving, and structural upgrading effects. In contrast, the effects of AI hardware on imported and exported intermediate goods are not significant.

This may be because AI software, such as algorithms, models, and data services, is essentially codified, possesses high portability and adaptability. Once an algorithm is developed, the marginal cost of replication and deployment is extremely low. This makes the increasing returns to scale effect of AI software significant. At the same time, AI algorithms can be embedded into existing management control systems and software without altering physical processes but optimizing decision-making. This uncertainty inhibits the stimulating effect of hardware AI innovation on the demand for intermediate goods.

### 7.2.2 Industry Heterogeneity

The secondary industry mainly includes mining and quarrying, manufacturing, electricity, gas and water supply, and construction. Other industries are not part of the secondary industry. To verify industry heterogeneity, the following regression models are constructed:

$$Y_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 AI_{ijt} * D_i + \alpha_3 Control_{ijt} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{36}$$

$$Y_{ijt} = \alpha_0 + \alpha_1 AI_{ijt} + \alpha_2 AI_{ijt} * D_j + \alpha_3 Control_{ijt} + \delta_{ij} + \mu_t + \varepsilon_{ijt} \tag{37}$$

where the dependent variables remain the demand for intermediate goods, intermediate goods imported from developing countries, and exported intermediate goods. $D_i$ and $D_j$ are industry dummy variables, representing whether the intermediate goods producing industry is the secondary industry and whether the intermediate goods using industry is the secondary industry, respectively. They take the value 1 if yes, and 0 otherwise.

Table 16: Industry Category Heterogeneity Test Results

| | All Goods | All Goods | Imports from Developing | Imports from Developing | Exported Goods | Exported Goods |
|---|---|---|---|---|---|---|
| AI | -0.042 | 0.494 | -0.013 | -0.013 | -0.021*** | 0.172* |
| | (0.378) | (0.841) | (0.012) | (0.039) | (6.791) | (0.143) |
| AI*$D_i$ | 9.732*** | | -0.757** | | 1.896*** | |
| | (2.202) | | (0.283) | | (4.615) | |
| AI*$D_j$ | | 7.057** | | -0.594* | | 1.266* |
| | | (3.876) | | (0.303) | | (0.613) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.904 | 0.903 | 0.906 | 0.893 | 0.936 | 0.928 |
| Adjusted $R^2$ | 0.168 | 0.158 | 0.276 | 0.301 | 0.322 | 0.236 |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes | Yes | Yes |

The results are shown in Table 16. From the production direction, for all intermediate goods and imported intermediate goods, the interaction term between AI innovation and the producing industry being the secondary industry is significant, while the coefficient of AI innovation itself is not significant. For exported intermediate goods, the interaction term between AI innovation and the producing industry being the secondary industry is significantly positive, while the coefficient of AI innovation itself is significantly negative. From the use direction, for total intermediate goods, imported intermediate goods, and exported intermediate goods, the interaction term between AI innovation and the using industry being the secondary industry is significantly positive.

The industry heterogeneity analysis shows that the secondary industry is the core sector for AI value creation. From the production direction, the interaction term between AI innovation and "producing industry is secondary industry" is significantly positive, while the coefficient of the AI patent itself is even negative. This highlights that pure AI knowledge output does not necessarily translate into economic value; it must be combined with the deep engineering capabilities, process knowledge, and industrial chain positioning of sectors like manufacturing. The quantifiable and optimizable characteristics of industrial production align highly with the data-driven nature of AI, allowing AI innovation to quickly translate into measurable efficiency gains, thereby directly stimulating demand for more advanced intermediate goods. From the use direction, the interaction term between AI and the using industry being the secondary industry is also significant in boosting demand for intermediate goods. This is because the economies of scale effect in industrial scenarios is pronounced; once validated, AI applications can be rapidly replicated, immediately reflected in enterprises' intermediate goods input structures and the competitiveness of their export products.

The heterogeneity results indicate that within industries, AI software innovations with strong generality and low marginal cost are the primary engines of efficiency improvement. Meanwhile, sectors like industry,Through their structured production processes, scale, and strong interlinkages, help transform AI innovation from knowledge into economic value.

# 8 Conclusions and Policy Implications

This paper demonstrates, both theoretically and empirically, how AI innovation acts upon the production network and trade structure of intermediate goods. From a joint perspective integrating technological innovation with the input-output of intermediate goods, it measures the inter-industry innovation flow table for AI and non-AI technologies. By constructing an intermediate goods-augmented technological progress model that distinguishes between AI innovation and non-AI innovation, it reveals the structural impact of AI, mediated through non-AI innovation, on the demand for intermediate goods. This provides reference significance for optimizing AI investment and financing strategies, improving policy support for AI development, and corroborating theoretical hypotheses related to AI.

The findings of this paper are as follows: First, in the intermediate goods market, AI innovation reshapes China's intermediate goods production network and trade structure through scale expansion effects, structural upgrading effects, and cost-saving effects. The flow of AI innovation significantly boosts the total demand for intermediate goods, especially the demand for domestic intermediate goods, strengthening the resilience of the domestic industrial chain. Concurrently, AI innovation drives the structure of intermediate goods imports to concentrate on high-tech products from developed countries, reducing dependence on intermediate goods from developing countries. On the export side, it significantly enhances the capacity of China's high-value-added intermediate goods to reach developed country markets, exhibiting a ladder-like upgrading characteristic of upward absorption and downward substitution. Second, AI innovation restructures the intermediate goods network by catalyzing non-AI innovation, propelling Chinese industries to higher positions in the global value chain. Mechanism analysis indicates that the promotional effect of AI on the use direction of non-AI innovation is a crucial mediating channel for driving the structural upgrading of intermediate goods and the elevation of global value chain positions. The more intensively an industry uses AI innovation, the higher its division of labor position in the global value chain, reflecting the endogenous and networked characteristics of AI-driven industrial upgrading. Third, AI algorithm and software innovation are the primary engines driving the reshaping of the intermediate goods market structure, while the effects of application system and hardware equipment innovation exhibit lags and conditionality. The secondary industry serves as the core channel for these effects; whether as a producer or user of AI innovation, its structured production activities and accumulation of industrial knowledge are key conditions for transforming AI potential into tangible economic benefits.

This study theoretically extends the analytical framework concerning AI innovation and the evolution of production networks, and empirically provides systematic evidence for China's industrial transformation in the AI era. The research conclusions indicate that China is not simply relying on external technology inputs. Instead, through the deep integration of AI with traditional industries, and by establishing the new before abolishing the old, it is internally fostering a more intelligent and resilient production network.

Based on the above conclusions, this paper proposes the following policy implications: First, consolidate the intelligent foundation of the domestic economic cycle. Policy should focus on building a batch of AI application scenario validation platforms, aggregating resources such as industrial algorithm libraries, industry-specific large models, and high-quality datasets, and opening them to small and medium-sized enterprises. This allows the catalytic effects of AI to spill over from leading enterprises to all links of the industrial chain. Simultaneously, encourage pairing between leading manufacturing enterprises and AI technology companies, support the secondary innovation process of codifying and modeling industry knowledge, and cultivate enabling service providers who "understand intelligence and are familiar with the industry." Furthermore, promote support tools like computing power vouchers, improve the national integrated computing power network, and facilitate the universal and easy availability of intelligent computing power supply. Second, optimize the upgrading path of the international cycle. On one hand, establish a guide for importing key AI technology products, identify high-tech intermediate goods that are deeply coupled with domestic applications and crucial for industrial chain security, provide customs clearance facilitation for such imports, and encourage upgrading buyer-seller relationships into technological cooperation relationships through joint R&D. On the other hand, package mature AI technologies into lightweight solutions and apply them to traditional export industries such as textiles and furniture. Help these industries enhance product quality while maintaining cost competitiveness, consolidating markets in developing countries and expanding into mid-to-low-end markets in developed countries. Third, focus on software-hardware synergy and industrial carriers. Policy incentives should tilt more towards AI industrial software R&D, industrial data rights confirmation and circulation, and the open-sourcing and sharing of algorithm models. Establish a first-version industrial software insurance compensation mechanism and a corporate chief data officer system to solve the problem of industrial data being "unwilling to share and reluctant to share." Simultaneously, select industrial sectors with long industrial chains, such as high-end equipment, electronic information, and new energy vehicles, to promote the implementation of AI in the entire process of design, production, and service. Pay attention to how AI optimizes the matching of upstream and downstream intermediate goods and reshapes chain-based production relations, maximizing the enabling effect within the industrial system. Fourth, lead AI cooperation in the Global South. Help developing countries bridge the intelligence divide through jointly building laboratories, providing public goods, and conducting talent training. Promote the application of Chinese technical standards and solutions in developing countries. Simultaneously, propose Chinese solutions on issues such as technical standards, cross-border data flows, and ethical norms, support the United Nations in playing a primary channel role in global AI governance, and create a stable and predictable external environment for domestic industrial development and global expansion.

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