SCIENTIFIC OASIS

International Journal of Economic Sciences

Journal homepage: www.ijes-journal.org
eISSN: 1804-9796

Artificial Intelligence and Enterprise Export Price Markup in China's Economy: Based on Large Language Models

Zhaosong Li [1], Weiwen Qian [2,*]

[1] Faculty of Business, Economics and Informatics, University of Zürich, Zurich, Switzerland
[2] Business School, University of Shanghai for Science and Technology, Shanghai, China

ARTICLE INFO

Article history:
Received 3 September 2025
Received in revised form 7 November 2025
Accepted 4 December 2025
Available online 16 December 2025

Keywords:
Artificial intelligence; Price markup; Economic upgrading; Staggered difference-in-differences; Large language models

ABSTRACT

China's exports face long-standing challenges of low quality, low price, and low profit margins. Amid intensifying global economic competition and deeper value chains, breaking the 'low-value-added lock-in' to boost export enterprises' profit margins is urgent for addressing foreign trade bottlenecks. This study systematically examines artificial intelligence (AI)'s effect and mechanism on export enterprises' price markup. It integrates 2007–2016 data from China's Customs Database and Shanghai and Shenzhen A-share manufacturing listed companies, combined with AI indicators built by extracting annual report text via large language models. Results show AI significantly raises export enterprises' price markup, with the 'intelligent empowerment' model having a stronger promotional effect than 'machine replacing human'. Mechanism analysis reveals AI's dual impacts: positive effects from efficiency improvement and technological innovation, and negative effects from intensified market competition and higher information transparency. Heterogeneity analysis finds AI benefits state-owned enterprises, high-productivity enterprises, quality-competitive enterprises, and those exporting to developed countries more. Additionally, it reduces markup dispersion and improves resource allocation efficiency. Overall, AI drives export enterprises to break low-value-added dilemmas, optimise resource allocation, and further boost China's export economy.

1. Introduction

Since the reform and opening up, China has rapidly developed into the world's factory by relying on its abundant labour resources and the advantages of scale expansion. However, with the accelerated reconfiguration of the global value chain, the traditional low-quality and low-price processing and export model has become unsustainable. On the one hand, the growth rate of domestic labor supply has slowed down, and the labor cost advantage that supports low-end manufacturing has gradually weakened. However, the international environment is becoming increasingly uncertain. Anti-globalisation sentiments are on the rise, trade frictions between China

* *Corresponding author.*
E-mail address: qww1022@126.com

https://doi.org/10.31181/ijes1512026255

and the United States continue to escalate, and geopolitical risks are rising, which poses significant challenges to China's trade transformation. The '14th Five-Year Plan for High-Quality Development of Foreign Trade' clearly states that it will promote quality, efficiency and power transformation in foreign trade and enhance the comprehensive competitiveness of foreign trade. In this context, it is imperative for Chinese enterprises to recalibrate their export competition strategies, moving from a cost-based competition model of 'thin profit but high sales volume' to a quality-focused approach of 'high quality and high price'. Price markup is an essential indicator for portraying the profitability of a firm using the ratio of a firm's product price to marginal cost to reflect the degree of deviation of product pricing from the marginal cost. The higher the price markup, the greater the company's pricing power in the market and the higher the monopoly profits it can earn [1]. Changing China's low-cost export competitive advantage, re-writing the label of 'low price and low quality', achieving export transformation and upgrading and enhancing the competitiveness of exports have become the focus nowadays.

Traditional corporate price markup strategies rely on static analyses of costs and markets [2]. The application of artificial intelligence (AI) by enterprises is changing the management logic of price markup and gradually becoming a key variable influencing pricing strategies. AI is currently the primary driving force behind industrial transformation and high-quality economic development. Its application in production and operation, market analysis, demand forecasting and other areas is becoming increasingly sophisticated. It has been demonstrated that this not only reshapes the cost structure and competitive mode of enterprises, but also has a profound impact on the price formation mechanism [3]. From the perspective of the action path, enterprises' application of AI can optimise production processes, precisely match supply and demand, reduce the cost of information asymmetry, thereby enhancing operational efficiency and product differentiation advantages, and providing support for the expansion of the price markup space [4]. Conversely, the popularisation of AI has also lowered the technical threshold and market entry barriers in some industries, which may attract more market entities to participate in the competition, intensify the price game within the industry, and instead restrict the increase of enterprise price markup [5]. This contradictory impact raises the core question: In the context of rapidly advancing AI, which is poised to transform various industries, it is pertinent to assess whether enterprises leveraging AI can effectively augment their price markup. What characteristics does its specific influencing mechanism present? Clarifying these issues will provide a theoretical and practical basis at the micro level for understanding the intrinsic connection between the application of AI and the price markup of enterprises.

Therefore, this paper utilises data from Chinese listed companies from 2007 to 2016, as well as data from Chinese customs, to investigate the impact and mechanism of AI on the price markup of export enterprises through the variable price model. It is very important to study the impact of AI on the price markup of export enterprises. This technology enables export enterprises to realize the strategic transformation from 'cost leadership' to 'value leadership', which has far-reaching significance to safeguard foreign trade earnings and promote the development of globalization, and is directly related to the reshaping of international competitiveness of enterprises and the rise of global value chain status.

In comparison with existing research, the innovative contributions of this study are primarily reflected in three aspects: Firstly, it is essential to overcome the limitations of single-effect analysis. A more comprehensive and logical review of the impact should be formulated, taking into account the two-way effect of AI on the price markup of enterprises. Secondly, the research conclusions can directly provide practical references for enterprises to solve the problem of low profits and promote the shift of product exports from cost-oriented to value-oriented, facilitating the deep integration of the digital economy and foreign trade.

The rest of this paper is structured as follows: Section 2 conducts a literature review. Section 3 focuses on theoretical research. Section 4 is devoted to research methods. Section 5 presents the results of empirical research. Section 6 carries out mechanism testing. Section 7 engages in further discussion. Section 8 outlines the conclusions and policy implications.

2. Literature review

There are two types of literature related to this paper.The first category is research on firms' price markup. Lerner [6] was the first to propose the Lerner index, which measures firms' price markup in terms of the degree of deviation of prices from marginal costs. At present, the primary methods for measuring price markups are the accounting method [7-8] and the production function method [9-10]. Scholars also explore the factors affecting price markup from two perspectives: first, using cost shocks as an entry point, e.g. Edmond *et al.*, [9] from the perspective of decreasing firm entry costs, it is found that free trade increases the degree of competition between firms and reduces their price markup. Scholars have also discovered that the development of the digital economy and competition from imported intermediate goods raise firms' cost pressure [11-12], which in turn suppresses firms' price markup. Second, focusing on changes in the competitive environment of enterprises, market competition [13], consumer familiarity with the product [14], product quality [15], local market size [2], and enterprise productivity [16] were found to be important factors affecting the price markup of enterprises.

The second stream of literature has explored how firms' AI influences trade. Freund *et al.*, [17] were the first to put forward that digital technology aids in eliminating information barriers between trading entities, thus expanding the network of trade links across countries and increasing trade flows and volumes. The factor of digital skills is increasingly taking the place of labor to become the key driver behind firms' production and export growth [18]. Given the dual background of actively promoting high-level opening up to the outside world and the continuously strengthening strategic position of AI, the application of AI in the field of international trade has also received extensive attention from scholars [19]. Maity *et al.*, [20] found that digital finance can significantly enhance the overall welfare of society. With regard to the expansion of enterprise exports, the application of AI has been shown to reduce costs and improve efficiency, thus promoting the expansion of enterprise export scale [21]. Brynjolfsson *et al.,* [22] suggested that the rollout of a new machine translation system on a digital platform led to a notable rise in international trade volume among related economic entities, with a recorded growth of 10.9%. Second, scholars investigated the role of AI in promoting the quality of export products [23]. Finally, the cost-reducing effect and innovation effect of AI have also raised the participation level and labor division position of the manufacturing industry in the global value chain [24], and enhanced the export productivity and technical complexity of the industrial sector [25-26].

To summarize the literature concerning the trade effects of AI, the focus of existing research is mainly on AI's positive impacts including improved production efficiency and broader market opportunities. Nevertheless, there is relatively little attention paid to the potential negative effects of AI in reshaping the patterns of market competition. These include the rise of new entrants due to falling technical barriers and ongoing R&D investment demands on businesses to maintain technological superiority. These factors could potentially constrain the price markup of enterprises. Meanwhile, existing research on the price markup of enterprises rarely incorporates the emerging technology variable of AI into the analytical framework. Additionally, there is a lack of systematic literature examining the inherent connection and operational mechanism between the application of AI and the price markup of export enterprises. In view of fact that export enterprises are facing a more complex international market environment and cost structure, and the current impact of AI on enterprises has gradually extended from optimising human resource costs to the entire chain, including production, marketing and supply chain management, against the backdrop of AI accelerating its empowerment of the foreign trade sector and promoting the transformation of export trade models, it is necessary to clarify how the application of AI affects the price enhancement of export enterprises. It is of great significance for helping export enterprises break through the traditional low-cost competition bottleneck and enhance their pricing power and core competitiveness in the international market by taking advantage of the technological dividend.

Compared with the existing literature, the marginal contributions of this paper are mainly reflected in the following three aspects: First, at the research perspective level, this paper is different from the existing literature in that it takes into account not only the positive impacts of AI on enterprises such as promoting efficiency improvement and technological innovation but also the negative impacts, including intensifying market competition and enhancing information transparency. Furthermore, the price markup is regarded as the net value manifestation of the combined effect of these two types of effects. The project will conduct a comprehensive analysis of the overall impact of price markup on export enterprises, as well as the internal logic underlying this impact. Secondly, at the theoretical research level, a variable price markup model will be constructed, with AI officially incorporated into the analytical framework of price markup for export enterprises. From the perspective of general equilibrium, the specific mechanism by which AI affects the price markup of export enterprises is analysed in depth, further enriching and expanding the theoretical system of research on the correlation between AI and the export behaviour of enterprises. Thirdly, at the level of research method, large language models are employed to characterise the intensity of enterprises' use of AI from multiple perspectives, including 'machine replacing human' oriented automation, 'intelligent empowerment' oriented intelligence, and the application of neutral basic technologies. At the same time, the calculation dimension of the enterprise price markup rate is extended to the ‘enterprise - product - destination country’ level. This study yields valuable insights into the impact of AI on the behavior of micro-enterprises, and provides refined empirical evidence for analyzing how AI influences the pricing power of export enterprises at the micro level.

3. Theoretical analysis and research hypothesis

3.1 Theoretical model

This paper incorporates the impact of AI on firms by drawing on the heterogeneous variable price markup model proposed by Melitz *et al.*, [27]. In this context, the consumer’s utility function takes the form of a quasi-linear utility function that includes a quadratic term, and it can be expressed as:

$$U = q_0^c + \alpha \int_{i \in \square} q_0^c di - \frac{1}{2}\gamma \int_{i \in \square} (q_i^c)^2 di - \frac{1}{2}\eta (\int_{i \in \square} q_i^c di)^2 \tag{1}$$

Assume that the set of goods is Ω, q_0^c is the consumption of the common product by consumers, and q_i^c is the consumption of the product i by consumers. The parameters α ,γ and η are positive numbers. η and α are the degree of consumer substitution between heterogeneous products, and γ is used to represent the heterogeneity among products. By solving the consumer optimisation problem, the demand function for the product i is obtained by using the marginal rate of substitution of consumers for the product $MRS_i = P_i$:

$$P_i = \alpha - \gamma q_i^c - \eta Q^c \tag{2}$$

Where $Q^c = \int_{i\in\Omega} q_i^c \, di$ is the total consumption of all commodities. Integrating the above equation over Ω yields the demand function for commodity i:

$$q_i = \frac{\alpha L}{\eta N + \gamma} - \frac{L}{\gamma} P_i + \frac{\alpha L}{\eta N + \gamma} \frac{L}{\gamma} P \quad (3)$$

In the Eq. (3), L is the total number of consumers in the market. Assuming that a total of Ω^* of the goods Ω is consumed, the domain of $q_i > 0$ is defined as $\Omega^* \in \Omega$. Assuming that N is the number of Ω^*, the average price index in the region is $P = 1/N \int_{i\in\Omega} P_i di$. Under monopolistic competition, the zero profit condition can be used to obtain the upper limit of prices in the region and the point at which firms stop production C_D:

$$P_{max} = \frac{1}{\eta N + \gamma} (\gamma \alpha + \eta N \bar{P}) \equiv C_D \quad (4)$$

The perspective is now shifted to firms and their cost function is assumed to be $TC_i = (\delta c_i / N^\lambda) q_i$. δ is used to capture the negative effect of local competitive factor market demand shocks on firms' costs and is assumed to be $\delta \geq 1$. λ denotes the extent to which a positive AI externality affects local firms. This externality is reflected in several aspects, for example, AI can enhance the interaction of enterprises in the region, which is conducive to promoting the accumulation of factors of production, cooperation and learning among enterprises in the region, and so on. Therefore, this paper assumes that the larger λ ($0 \leq \lambda < 1$) is, the greater the impact of AI on the positive externality of enterprises. By solving the enterprise profit maximisation problem, the price P_i and the corresponding sales volume q_i faced by the enterprise are deduced as:

$$P_i = \frac{\alpha \gamma}{2(\eta N + \gamma)} + \frac{\eta N}{2(\eta N + \gamma)} \overline{P} + \frac{c_{i+}\delta_i}{2N^\lambda} = \frac{1}{2}(C_D - \frac{\delta c_i}{N^\lambda}) \quad (5)$$

$$q_i = \frac{\alpha L}{\eta N + \gamma} + \frac{\eta N}{2(\eta N + \gamma)} \frac{L}{\gamma} \overline{P} - \frac{L}{\gamma} \frac{c_{i+}\delta_i}{N^\lambda} = \frac{1}{2} \frac{L}{\gamma} (\delta_i - \frac{\delta c_i}{N^\lambda}) \quad (6)$$

The cost of a firm, on the other hand, consists of two items: the fixed cost f_E that a firm needs to pay to enter the market; and the variable cost of the firm δc_i. Among them, δc_i obeys the Pareto distribution, i.e. $G(c) = (c/c_M)^k$, $c \in [0, c_M]$. The established literature finds that AI attracts more firms and significantly promotes new firm entry [28]. Therefore, this paper assumes that f_E is negatively related to AI. Under the condition of free entry of firms in a monopolistically competitive market, firms expect a profit of 0, there is:

$$\int_0^{C_D N^\lambda} \pi(c) dG(c) - f_E = \frac{L}{4\gamma} \int_0^{C_D N^\lambda} (C_D - \frac{c}{N^\lambda})^2 dG(c) - f_E = 0 \quad (7)$$

Therefore, the critical cost value of the firm is:

$$C_D = [\frac{2\gamma \ \ (k+2)(k+1) c_M^k f_E}{L(N^\lambda)^k}]^{\frac{1}{k+2}} \quad (8)$$

From Eq. (8), it can be further deduced that the average price of a firm is proportional to the value of the firm's critical cost C_D, which in turn is a decreasing function of the number of firms. Therefore, the price space of incumbent firms also decreases as the number of firms increases. Thus, if AI increases the number of firms, the price space faced by firms will decline. Further, combining this with the zero profit condition, the price markup at equilibrium Λ_i can be obtained as:

$$\Lambda_i = \frac{P_i - MC_i}{P_i} = 1 - 2(\delta c_i)/\{[\frac{2\gamma\ (k+2)(k+1)c_M^k f_E}{L(N^\lambda)^k}]^{\frac{1}{k+2}} N^\lambda + \delta c_i\} \tag{9}$$

According to Eq. (9), the impact of AI on the price markup of enterprises Λ_i involves three parameter values: (1) The size of λ. It is used to represent the positive externality brought by AI application to enterprises, and it can be inferred from Eq. (9) that the price markup of enterprises is proportional to λ, $\partial\Lambda_i/\partial\lambda > 0$, i.e., the spillover effect. (2) The size of f_E, $\partial\Lambda_i/\partial f_E > 0$. It represents the impact of AI on the threshold of enterprises entering and exiting the market. When f_E falls as a result of AI application, the price markup of the firm will also fall. (3) The size of δ. Firms' price markup becomes a decreasing function of firms' variable costs δc_i, so when δ increases, firms' price markup is also negatively impacted. In this paper, the above negative effects of AI on firms' price markups are collectively referred to as competition effects.

Therefore, the following inference is drawn: the ultimate direction of the impact of AI on the price markup of firms will depend on the net effect of the competition and spillover effects. If the competition effect is greater than the spillover effect, the firm price markup will fall, and conversely, the firm price markup will rise.

3.2 Mechanisms study

Based on the theoretical model, this paper argues that the AI of firms affects the price markup of exporters mainly through the positively facilitated productivity-enhancing effect, the technological innovation effect, and the negatively inhibited competition-intensifying and transparency-enhancing effects, as shown in Figure 1 below.

3.2.1 Positive mechanisms: efficiency improvement and technological innovation effects

Efficiency improvement effect: Firstly, the application of AI by enterprises can significantly enhance production and operational efficiency. By leveraging automated equipment such as industrial robots and intelligent assembly lines, as well as production process optimisation algorithms, high-precision and uninterrupted standardised operations can be achieved, significantly enhancing the output and quality stability of export products [29]. Furthermore, human errors can be reduced, resource allocation optimised, energy consumption and raw material loss lowered, and unit production costs reduced. Conversely, high-quality products are more likely to meet the technical standards and market demands of various countries, creating greater space for international pricing and thereby increasing the price markup. Secondly, the implementation of AI has been shown to enhance the efficiency of decision-making and market connection for export enterprises. By leveraging its extensive big data processing and machine learning capabilities, enterprises can seamlessly integrate global supply chain, target market demand and competing product price information in real time. This enables the formulation of scientific production and inventory plans, as well as the control of production equipment and product quality through intelligent monitoring systems [30]. Thirdly, cross-border marketing tools such as multilingual intelligent customer service and precise user profiling enabled by AI help enterprises connect with global customers, precisely promote brands, and quickly collect overseas feedback to iterate products. This data-driven model enhances production efficiency and enables the company to flexibly respond to changes in the international market and match overseas demands [31]. It facilitates the completion of export transactions at favourable prices and increases the price markup, which leads to Hypothesis 1: AI increases the price markup of export enterprises through the efficiency improvement effect.

Technological innovation effect: Firstly, the implementation of AI has been shown to accelerate the product innovation and iteration of export enterprises. By leveraging machine learning capabilities to analyse global market demands, consumption trends and technological frontiers, enterprises can accurately identify the segmented demands of different countries and regions. For instance, they can develop low-carbon products for markets with strong environmental awareness and research and develop highly adaptable components for the smart device field. Concurrently, AI-assisted R&D and design tools, such as virtual simulation and parameter optimisation algorithms, have the potential to reduce the product development cycle, minimise trial-and-error expenses, and encourage the establishment of competitive advantages in terms of functionality, performance or user experience for products. Such innovative products enhance market competitiveness and increase product added value, helping enterprises secure a higher pricing space [32]. Secondly, the integration of AI is instrumental in driving the technological innovation and upgrading of export enterprises' operations. In the context of cross-border supply chains and quality control processes, the AI-enabled intelligent traceability system has the capacity to comprehensively track product data from production to delivery. This capability fulfils the rigorous demands of the international market for product traceability and compliance. Intelligent logistics scheduling algorithms can optimise cross-border transportation routes, dynamically adjust inventory, and reduce logistics losses and costs. Furthermore, AI quality inspection technology can achieve real-time identification and control of product defects, ensuring the stability of export product quality [33]. These technological innovations not only enhance the compliance capabilities and risk response efficiency of enterprises, but also strengthen the market trust of products, further supporting the increase in price markup, leading to Hypothesis 2: AI increases the price markup of export enterprises through the effect of technological innovation.

3.2.2 Negative mechanisms: market competition and information transparency effects

Market competition effect: While the implementation of AI has indeed enhanced the efficiency of production and innovation for export enterprises, it has concomitantly led to heightened market competition and restrictions on price markups. Firstly, the widespread adoption of AI technology has led to a significant reduction in the industry's entry barriers, resulting in a substantial increase in the number of market competitors [34]. As the cost of AI tools declines and their ease of use improves, more small and medium-sized enterprises can quickly introduce AI technology to optimise their operations. They can possess the basic capabilities to compete with leading enterprises without the need for long-term accumulation of high technological investment, thus weakening the entry barriers formed by technology and capital in traditional industries. The increase in competitors has led to heightened market competition. In order to maintain their market share, some enterprises have no choice but to lower their prices and reduce the space for price markups [35]. Secondly, the integration of AI within business operations has been shown to enhance the speed at which enterprises respond to market trends and competitors. By leveraging AI-driven market monitoring tools, enterprises can swiftly capture competitor strategic changes, such as pricing adjustments and product iterations, and formulate agile response plans. Conversely, strategic adjustments made by one party are quickly perceived and responded to by the opponent [36]. This rapid offensive and defensive competitive situation intensifies the price game and further weakens the ability of enterprises to maintain high price markups, leading to Hypothesis 3: AI has been shown to reduce price markups of export enterprises, with market competition being a key factor in this effect.

Information transparency effect: Firstly, AI-supported information aggregation and analysis platforms, such as cross-border e-commerce price comparison systems and global supply chain data platforms, enable global customers and intermediaries to swiftly access information such as product prices, specifications, and delivery cycles of different export enterprises, facilitating straightforward multi-dimensional comparisons [37]. The enhancement of information transparency has intensified price competition. Enterprises encounter challenges in maintaining high pricing due to information gaps, leading to a narrower margin for price markups. Secondly, AI promotes the transparency of enterprise cost and operational information. The implementation of AI-driven supply chain traceability systems and cost accounting tools has the dual benefits of enhancing the accessibility of core data for regulatory authorities and partners, such as production costs and logistics expenses, while also fostering the establishment of more transparent pricing rules within the industry. In order to maintain competitiveness, enterprises may need to consider additional investments in order to optimise their cost structures, which may in turn increase operational pressure. Thirdly, AI-enabled consumer feedback systems, such as intelligent evaluation and analysis systems and cross-border after-sales tracking platforms, facilitate market access to information such as product quality and service levels. There has been a notable increase in consumers' demand for product quality and compliance [38]. Enterprises need to increase investment to improve the quality control system and obtain international certifications to meet the demands. This additional cost has a further impact on the price markup, leading to Hypothesis 4: AI has the potential to reduce the price markup of export enterprises by enhancing market transparency.

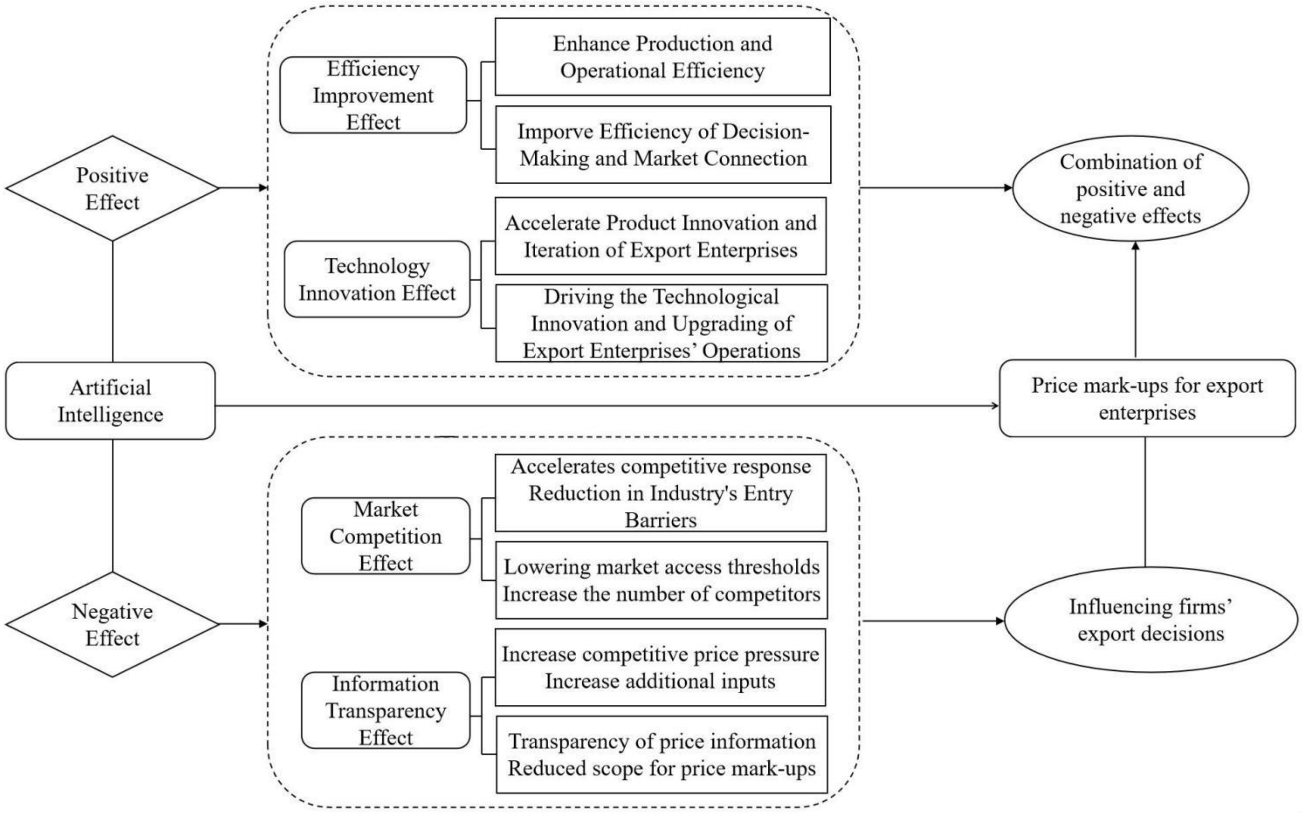

Fig. 1. Mechanisms Underlying the Impact of AI on the Price Markup of Export Enterprises

4. Method and data sources

4.1 Modelling

To measure how AI affects the price markups of export enterprises, and based on the previous theoretical analysis, this study adopts a staggered difference-in-differences (DID) model for empirical testing. Enterprises not using AI are taken as the control group, whereas enterprises applying AI to any extent form the treatment group. The specific form of the model is as follows:

$$Markup_{fkjt} = \alpha + \beta AI_{ft} * post_{ft} + \gamma \sum Control_{kjt} + \delta_{fk} + \delta_{jk} + \delta_{fj} + \delta_{kt} + \varepsilon_{fkjt} \tag{10}$$

Where f, k, j and t denote the enterprise, product, destination country and year respectively. The explanatory variable $Markup_{fkjt}$ is the price markup of enterprise, the core explanatory variable AI_{ft} is the degree of AI of the enterprise f in the year t; $Control_{kjt}$ represents the control variables. This paper also controls the two–dimensional combination of the enterprise–product fixed effect δ_{fk}, the two–dimensional combination of the destination country–product fixed effect δ_{jk}, and the firm–destination country fixed effects δ_{fj}, and further controls for product–year fixed effects δ_{kt}, so as to control for all individual effects related to firms, products and destinations that do not change over time; ε_{fkjt} is the error term, and β is the core estimation parameter representing the net effect of the impact of firms' AI on the price markup of enterprises.

4.2 Variable description

1. Explanatory variable: price markup of product exported by the enterprises ($Markup_{fkjt}$). This paper draws on De Loecker *et al.*, [10] to calculate the markup rate of products. The specific model is formulated as follows:

$$\mu_{ft} = \theta_{ft}^{m}(\alpha_{ft}^{m})^{-1} \tag{11}$$

Where α_{ft}^{m} denotes the share of expenditure on intermediate material input factors, i.e. the ratio of the cost of intermediate material input factors to total sales, which can be calculated directly from firm-level data. θ_{ft}^{m} denotes the output elasticity of intermediate material input factors, which needs to be estimated from the production function under the condition of controlling for unobservable productivity shocks. In order to obtain unbiased estimates of output elasticities, this paper uses a more flexible transcendental logarithmic production function in the production function setting:

$$\begin{aligned} Y_{ft} &= \beta_l l_{ft} + \beta_k k_{ft} + \beta_m m_{ft} + \beta_{ll} l_{ft}^2 + \beta_{kk} k_{ft}^2 + \beta_{mm} m_{ft}^2 + \beta_{lk} l_{ft} k_{ft} + \beta_{km} k_{ft} m_{ft} \\ &+ \beta_{lm} l_{lt} m_{ft} + \beta_{lkm} m_{lt} k_{ft} m_{ft} + \omega_{ft} + \varepsilon_{ft} \end{aligned} \tag{12}$$

Where Y_{ft} ,l_{ft} ,k_{ft} and m_{ft} denote the natural logarithms of gross output, labour, capital and intermediate material inputs respectively, ω_{ft} denotes the heterogeneous productivity of firms, and ε_{ft} is the error term. Considering the endogeneity between variable factor inputs and productivity, this paper adopts the ACF two-step method to estimate the above productivity function. A non-parametric regression is performed on its lagged term to obtain the productivity stochastic shock $v_{ft}(\beta)$, and then the generalised moment estimation is used to obtain the corresponding parameter estimates of the productivity function to compute the output elasticity θ_{ft}^{m}, which then yields the price markup of the exporting firms. The price markup is further calculated at the product-destination level.

Assumptions N product ($N = \sum_{k\in\Omega} k_j$) is produced by f firm in the t year , and since the product category N is set to the HS6-digit product-destination level in this paper, the subscripts k and j can be replaced by N in the equations below. This results in $N + 1$ equations to calculate $N + 1$ unknown quantities.

$$\varphi_{f1t} = \varphi_{ft} + \alpha_{ft}\rho_{f1t} + b_{ft}\rho_{f1t}^{2} + c_{ft}\rho_{f1t}^{3}$$
$$\cdots \tag{13}$$
$$\varphi_{fNt} = \varphi_{ft} + \alpha_{ft} + b_{ft}\rho_{fNt}^{2} + c_{ft}\rho_{fNt}^{3}$$

$$\sum_{h\in\Omega}\rho_{fkjt} = \frac{exp_{ft}}{imp_{ft}} \tag{14}$$

After calculating the distribution coefficient ρ_{fkjt}, the output elasticity of the variable factors of production can be obtained, which in turn leads to the price markup of the product k produced by the enterprise f in the year t exported to the country j:

$$\mu_{fkjt} = ln(\theta_{fkjt}\frac{P_{fkjt}Q_{fkjt}}{exp(\rho_{fkjt})P_{ft}^{v}Q_{ft}^{v}}) \tag{15}$$

Explanatory variable: AI (AI_{ft}). To more accurately measure the level of AI application in enterprises, we adopt a text analysis method based on the ERNIE large language model, with the specific steps as follows. The specific list of AI keywords, please refer to Appendix I (Table A1).

Step 1: Identify Text Objects and Construct a Corpus. We chose two sections from the annual reports of listed companies to serve as the core text sources: 'Management Discussion and Analysis (MD&A)' and 'Table of Contents, Glossary and Major Risk Factors', covering the time span from 2006 to 2020. The original text was split into individual sentences using periods and semicolons, forming a raw sentence database. To enhance the representativeness of the corpus, we constructed a sentence library to be annotated through two methods: (1) Extracting sentences containing AI-related keywords under the two categories of 'machine replacement' and 'intelligent empowerment' (e.g., 'industrial robots', 'machine learning', 'predictive maintenance', 'computer vision'); (2)Conducting stratified random sampling by year to ensure a balanced number of sentences across all years. Ultimately, an annotated corpus was formed.

Step 2: Manual annotation and quality control. The research team manually labeled the sentences in the corpus. The labeling system includes three categories: AI technology (further distinguishing between 'machine replacing human' and 'intelligent empowerment'), non-AI digital technology (such as blockchain, common information technology terms, etc.) and non-digital technology. During the annotation process, a two-person back-to-back annotation and dispute arbitration mechanism is implemented to ensure the consistency and reliability of the labels, ultimately forming high-quality training sets, validation sets and test sets.

Step 3: Train the ERNIE model and perform sentence prediction. Fine-tune the ERNIE model with labeled corpora to accurately identify whether a sentence expresses the application of AI technology by an enterprise and determine the specific type of technology ('machine replacing human' or 'intelligent empowerment'). Model training focuses on accuracy and F.8-Score to reduce the risk of false alarms. After the training is completed, the model is used to predict all the sentences in the annual report and output the technical label of each sentence.

Step 4: Based on the ERNIE large language model, predictions are made for each sentence in the 2007–2016 sentence library to be predicted. The core is to determine whether the enterprise has applied AI and whether it involves two types of AI application models: 'machine replacing human' or 'intelligent empowerment'. Based on the ERNIE large language model, predictions are made for each sentence in the 2007–2016 sentence library to be predicted. If the text of the enterprise in the current year contains expressions related to 'machine replacing human' applications, such as the replacement of automated equipment and the operation of unmanned workshops, or related to 'intelligent empowerment' applications, such as data-driven decision-making and the construction of intelligent collaborative platforms, if either type of AI application expression is present, it is determined that the enterprise has adopted AI, and the indicator is assigned a value of 1. If neither of the two types of application expressions appears, it is determined that the enterprise has not applied AI. and the indicator is assigned a value of 0. This paper examines overall usage intensity of AI in enterprises (AI_{ft}), the automated orientation model of replacing humans with machines (AI_robot_{ft}), and the intelligent empowerment orientation model (AI_int_{ft}).

3. Control variables. The firm level includes: the size of the firm, which is expressed as the logarithm of the number of employees in the firm; age_{ft} denotes the duration of a firm's export operations, measured by the number of years the firm has engaged in exporting activities. Variables at the destination country level are defined as follows: $pgdp_{jt}$ represents the importing country's per capita income level, used to gauge the country's consumption level and hierarchy; $open_{jt}$ is expressed as the ratio of the importing country's total imports and exports to its gross domestic product (GDP), serving to measure the country's degree of external economic connection; $exchange_{jt}$ is converted using the U.S. dollar as an intermediary, included to control for the impact of trade costs; $tariff_{jt}$ is measured by the tariff rates corresponding to HS6-digit products, intended to control for the impact of tariff barriers; $distance_{jt}$ refers to the geographic distance between China and the capital city of the importing country, included to control for the trade costs associated with product trade with the importing country.

3.3 Data description and descriptive statistics

The data spanning 2007–2016 used in this paper's empirical research includes the China Customs Database, China Market & Accounting Research Database (CSMAR), RESSET Financial Research Database, and the annual reports of listed companies. For the control variables, data on importing countries' per capita GDP, degree of openness, product tariffs, and exchange rates are sourced from the World Bank Database, while data on geographical distance is obtained from CEPII-GeoDist. Table 1 presents the definitions of variables and their descriptive statistics.

Table 1
Variable definitions and descriptive statistics

Variable Type	Variable Name	Variable Symbol	Obs	Mean	SD	Min	Max
Explained Variable	Price markup	*Markup*	6860	-0.034	3.472	-9.794	12.923
Policy Variable	Artificial intelligence	*AI*	6860	0.684	1.346	0.000	4.510
Control Variable	Enterprise	*size*	6860	7.641	1.075	5.036	10.711
	Enterprise Export	*age*	6860	2.592	0.392	0.693	3.367
	GDP per capita	*pgdp*	6860	1.589	1.119	0.003	3.884
	Openness	*open*	6860	0.732	0.409	0.273	1.821
	RMB exchange	*exchange*	6860	60.014	135.623	0.122	4425.306
	Importing country tariffs	*tariff*	6860	0.044	0.037	0.000	0.500
	Distance	*distance*	6860	15.964	5.963	7.539	19.744

5. Empirical findings

5.1 Baseline regression results

The benchmark regression results are shown in Table 2. Columns (1) to (3) illustrate the impact effects of the overall usage intensity of AI in enterprises, the 'machine replacing human' automation-oriented model, and the 'intelligent empowerment' intelligence-oriented model on the price markup of export enterprises. As illustrated in Column (1), the regression coefficient of *AI*post* is positive at the 1% significance level, indicating that the overall usage intensity of AI can significantly enhance the price markup of export enterprises. In columns (2) to (3), the regression coefficients of the 'machine replacing human' automation-oriented model and the 'intelligent empowerment' intelligence-oriented model are significantly positive, and the 'intelligent empowerment' model has a greater promoting effect on the price increase of export enterprises than the 'machine replacing human' model. By leveraging AI technology, export enterprises can access real-time data and in-depth insights into global market trends, enabling them to optimise their price markup strategies. On the one hand, AI integrates multi-dimensional information such as cross-border transaction data, fluctuations in target market demand, pricing dynamics of competing products, and exchange rate changes through its big data analysis capabilities, helping enterprises discover key clues such as the price affordability of niche markets and differences in consumer preferences. Conversely, AI-driven dynamic pricing models have the capacity to respond in real time to fluctuations in the international market. For instance, pricing plans can be rapidly updated based on order volume, inventory levels, and tariff policies, enhancing the enterprise's ability to respond to market changes.

Table 2
Benchmark regression results

	Markup (1)	Markup (2)	Markup (3)
*AI*post*	0.3515*** (0.1333)		
*AI_robot*post*		0.0382*** (0.0101)	
*AI_int*post*			0.0552*** (0.0033)
size	0.2332* (0.1221)	0.0008* (0.0005)	0.0206*** (0.0011)
age	0.0187* (0.0103)	0.1140*** (0.0151)	0.0706*** (0.0026)
pgdp	0.0017 (0.0169)	0.0270*** (0.0095)	0.0257** (0.0102)
open	0.0084*** (0.0014)	0.0064*** (0.0009)	0.0146*** (0.0048)
exchange	-0.3214*** (0.0946)	-0.0640*** (0.0065)	-0.0054 (0.0036)
tariff	-0.0232* (0.0122)	-0.0055** (0.0025)	-0.0438*** (0.0117)
distance	-0.0106** (0.0046)	-0.0132*** (0.0024)	-0.0153*** (-0.0011)
cons	-0.0246*** (0.0038)	-0.0063*** (0.0006)	-0.0180*** (0.0039)
Firm–Product Fixed Effects	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES
R^2	0.1734	0.1346	0.2834
N	6860	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

5.2 Endogenous tests

Considering that exporters with high price markups may proactively adopt AI, a potential two-way causality issue arises. To mitigate this potential reverse causality problem, this study employs the two-stage least squares (2SLS) method and selects two instrumental variables to conduct endogeneity tests. This paper selects new IV variables.

First, the average AI adoption level of other enterprises within the same industry as the focal enterprise is selected as an instrumental variable. The rationale for this selection is based on two considerations: (1) The AI adoption process of an enterprise is significantly influenced by the technical characteristics and development trends of its industry, and there are systematic differences in the level of AI application across different industries. (2) A peer effect exists in AI adoption among enterprises within the same industry, leading to similarities in the AI application levels of enterprises in the same industry. This instrumental variable is highly correlated with the focal enterprise's AI adoption level, while it does not directly affect the enterprise's export price markup—thus satisfying the exogeneity requirement for instrumental variables.

Secondly, referring to the research framework of Bartik [39] and Goldsmith-Pinkham *et al.*, [40], this paper uses the moving average share method to construct Bartik instrumental variables. This variable is constructed by interacting the average AI adoption level of enterprises in the same industry within the city where the focal enterprise is located (an exogenous variable) with the growth rate of Internet broadband users in the prefecture-level city (a common impact factor) in the initial year of the sample period. The industry average AI adoption level in the initial year reflects the initial conditions of enterprises' AI application, while the growth rate of broadband users reflects the dynamic development of urban digital infrastructure, an essential foundation for enterprises to adopt and implement AI. The combination of the two not only ensures a high correlation between the instrumental variable and the focal enterprise's AI adoption level, but also effectively severs the direct interference of the instrumental variable on export price markup through the interaction of exogenous initial conditions and common shocks, thereby complying with the exclusivity constraint of instrumental variables.

Table 3 presents the results of the endogeneity test. After selecting appropriate instrumental variables and conducting the endogeneity test, the positive impact of enterprises' AI on the price markup of export enterprises remains statistically significant and robust.

Table 3
Results of endogenous test

	The average level of AI of other enterprises in the same industry		Moving average share method	
	First Stage (1)	Second Stage (2)	First Stage (3)	Second Stage (4)
IV	0.0036^{***} (0.0004)		0.0106^{**} (0.0046)	
*AI*post*		0.0047^{***} (0.0019)		0.0063^{***} (0.0004)
Control	YES	YES	YES	YES
cons	0.0009 (0.0010)	-0.0054 (0.0047)	-0.0026^{***} (0.0007)	-0.0120^{***} (0.0040)
Firm–Product Fixed Effects	YES	YES	YES	YES

Table 3
Continued

	The average level of AI of other enterprises in the same industry		Moving average share method	
	First Stage	Second Stage	First Stage	Second Stage
	(1)	(2)	(3)	(4)
Destination–Product Fixed Effects	YES	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES	YES
Kleibergen-Paap rk LM		1153.567		968.468
		(0.000)		(0.000)
Kleibergen-Paap rk Wald F		1673.574		1379.568
		(16.57)		(29.57)
N	6860	6860	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

5.3 Robustness tests
5.3.1 Substitution of variables
To further reduce biases in variable measurement, this paper uses text analysis to construct an indicator of enterprise AI application intensity. Using Python web crawlers, we download and collect annual report text data of A-share listed companies in the Shanghai and Shenzhen stock markets from the 'Juchao' Information Network, forming an initial dataset for screening. Drawing on Yao *et al.*, [41] we develop a list of 73 AI-related feature words, including machine translation, computer vision, human-computer interaction, deep learning, neural networks, biometric recognition, data mining, and speech synthesis. Using the 'jieba' word segmentation tool, we search for and match these feature words in the annual reports, then calculate their total frequency. The AI application indicator is defined as the natural logarithm of one plus the total frequency of these AI-related terms (*Lnwords*). This approach addresses the limitations of previous studies that relied on dummy variables, captures differences in the degree of AI application, and creates a more suitable data foundation for fixed-effect quasi-natural experiments. As shown in column (1) of Table 4, the results are consistent and robust.

5.3.2 Sample shrinkage and truncation treatment
To effectively mitigate the impact of outliers on estimation results, this study refers to the method of Crinò *et al.*, [42] and conducts bilateral winsorisation and bilateral truncation on the sample. As presented in Columns (2) and (3) of Table 4, the coefficient of *AI*post* is largely consistent with the baseline regression results in terms of magnitude, sign, and significance level. This further confirms the reliability of our benchmark regression findings.

5.3.3 Model of intervention effect
As firms' AI is decision-generated and not entirely exogenous from random groupings, firms with large exports and good business conditions may be more likely to undergo AI application, which in turn leads to biased estimation results. In order to mitigate the selection bias of firms' AI, the policy dummy variables are modeled, the inverse Mills ratio is introduced, and an intervention effect model is constructed accordingly, where the selection equation is:

$$D^* = \alpha + \delta Z'_{fkjt} + \varepsilon_{fkjt} \tag{16}$$

In Eq.(16), $AI \times post \neq 0$, when $D^* \geq 0$, otherwise $AI \times post = 0$; Z'_{fkjt} is the explanatory variable of whether AI has been carried out. Since the enterprise export scale and enterprise technology innovation level are important influencing factors of whether the enterprise carries out AI technology, this paper selects the enterprise's export volume and the number of patents acquired by the enterprise as the explanatory variables Z'_{fkjt}. Among them, the regression results of the intervention effect model are shown in columns (4) and (5) of Table 4. After taking into account the selection bias of firms' AI, the policy effect remains significantly positive at the 1% level and the obtained results remain robust.

Table 4
Replacement variables, sample shrinkage and truncation treatments, intervention effects models (robustness tests)

	Replacement Variables	Sample Shrunk	Sample Truncated	Value of firms' exports	Number of patents acquired by firms
	(1)	(2)	(3)	(4)	(5)
*AI*post*	0.5956***	0.6529***	-0.3006***	0.0989***	-.01737***
	(0.2174)	(0.1321)	(0.0656)	(.0344997)	(0.0039)
Control	YES	YES	YES	YES	YES
cons	2.1219***	-1.7865***	1.0522***	-1.3669***	-0.7842***
	(0.0426)	(0.1295)	(0.0145)	(0.1566)	(0.0115)
Firm–Product Fixed Effects	YES	YES	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES	YES	YES
R^2	0.0371	0.0562	0.1266	0.1466	0.2758
N	6860	6860	6860	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

5.3.4 Common trend hypothesis testing

Following the approach of Beck *et al.,* [43], this study examines the dynamic changes in the price markup of enterprises before and after AI application. If the enterprise's price markup showed no significant improvement prior to AI adoption, but experienced a significant increase after AI application, this indicates that the improvement in price markup is indeed driven by the enterprise's AI adoption. This further confirms that the conclusions derived from the benchmark regression are credible. Considering the limitation of data length, this paper selects 4 years before AI application and 2 years after AI application to test the dynamic trend. This paper sets dummy variables of $Year-4$ -$Year2$ for a total of six years, and establishes a fixed effects model as shown below:

$$Y_{fkjt} = \alpha + \beta_1 Year_{fkjt}^{-4} + \beta_2 Year_{fkjt}^{-3} + \ldots + \beta_5 Year_{fkjt}^{1} + \beta_6 Year_{fkjt}^{2} + \gamma \sum Control_{kjt} + \lambda_{ft} + \lambda_{kt} + \lambda_{jt} + \varepsilon_{fkjt} \tag{17}$$

In Eq. (17), β_1-β_6 are the coefficients to be estimated for the dynamic trend test and other variable is the same as Eq. (17). Table 5 shows that before enterprises adopted AI, there was no significant difference in the outcome variable between the treatment group and the control group.

This confirms that the 'common trend' hypothesis is satisfied. At the same time, the average intervention effect after AI application is significant and has a certain continuity.

Table 5
Common Trend Hypothesis Testing and dynamic Effects Estimation (Robustness test)

	Markup	Markup
	(1)	(2)
Year-4	-0.0192	-0.0108
	(0.0159)	(0.0097)
Year-3	-0.0014	-0.0025
	(0.0017)	(0.0048)
Year-2	-0.0009	0.0030***
	(0.0025)	(0.0020)
Year-1	-0.0007	-0.0040***
	(0.0010)	(0.0052)
Year1	0.0105***	0.0091***
	(0.0028)	(0.0034)
Year2	0.0689***	0.01261**
	(0.0213)	(0.0046)
Control	YES	YES
cons	0.4252***	-0.1081***
	(0.0158)	(0.0216)
Firm–Product Fixed Effects	NO	YES
Destination–Product Fixed Effects	NO	YES
Firm–Destination Country Fixed Effects	NO	YES
Product–Year Fixed Effects	NO	YES
R^2	0.2646	0.3723
N	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

5.3.5 Placebo testing

In order to exclude the interference of unobservables in the staggered double-difference model, drawing on Chetty *et al.*, [44] samples were randomly selected as the treatment group and the remaining samples were reallocated to the control group, and the baseline regression was performed again. The above process was repeated 500 times, and the coefficients and corresponding p-values obtained from each regression were recorded, as shown in Figure 2.

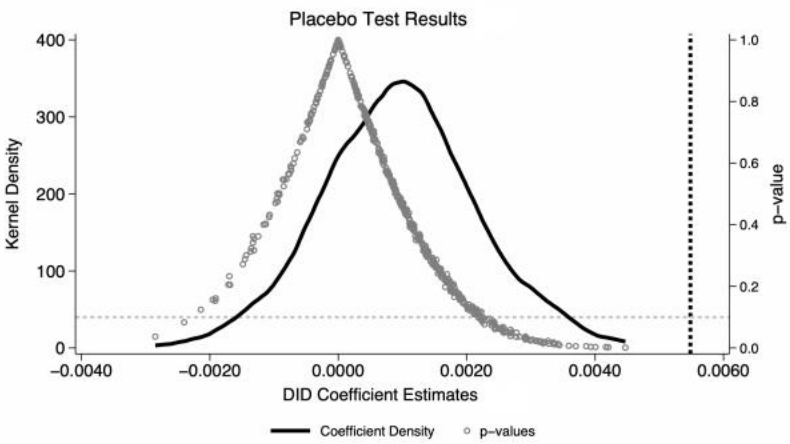

Fig. 2. Placebo test

This result is identified as an outlier in the placebo test. Nevertheless, this outcome indicates that the results of the benchmark regression are less likely to be affected by unobservable factors, and thus the conclusions derived remain robust.

5.4 Heterogeneity tests

5.4.1 Heterogeneity of enterprise ownership

The above analysis shows that AI exerts a notable impact on the export price markup of Chinese enterprises. However, this conclusion does not account for the fact that AI’s effect on export price markup may differ across enterprises of varying ownership types due to differences in organizational structure, resource endowment, decision-making mechanisms, and other factors. To address this, this paper categorizes the sample into state-owned enterprises (SOEs) and non-state-owned enterprises based on ownership type. The estimation results are presented in columns (1)–(2) of Table 6. As shown in the table, AI has a significantly positive impact on the export price markup of state-owned enterprises, whereas its impact on the export price markup of non-state-owned enterprises is not statistically significant.

Table 6
Heterogeneity test results by enterprise ownership and level of economic development of export destination countries

	Types of enterprise ownership		Level of economy development of export destination countries	
	State-owned enterprises	Non-state-owned enterprises	Developed countries	Developing countries
	(1)	(2)	(3)	(4)
*AI*post*	0.2929^{***}	0.1131^{***}	0.8646^{***}	0.0006
	(0.0169)	(0.1256)	(0.0977)	(0.0026)
Controls	YES	YES	YES	YES
cons	-2.6152^{***}	1.4190^{***}	-3.2485^{***}	-3.8927^{***}
	(0.0315)	(0.0958)	(0.1158)	(0.0485)
Firm–Product Fixed Effects	YES	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES	YES
Firm–Destination Country Fixed	YES	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES	YES
R^2	0.4146	0.5923	0.5331	0.4724
N	3633	3227	3521	2855

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

AI has had a considerable impact on the production and operational efficiency, as well as the resource integration capabilities, of state-owned enterprises. By optimising manufacturing processes through intelligent production systems and precisely matching international market demands through big data analysis, it has effectively strengthened the non-price competitive advantages of products, thereby supporting the increase in export price markups. State-owned enterprises have inherent advantages in terms of technological research and development investment, cross-border resource acquisition and policy support, and can fully leverage the technological dividends of AI. For instance, the company has leveraged an AI-driven supply chain traceability system to meet international market compliance requirements and has relied on intelligent marketing tools to build a high-end brand image. These measures have helped the company gain a higher space in international pricing and promote the increase of price markups. In contrast, non-state-owned enterprises have the potential to enhance operational efficiency and reduce certain production costs through the implementation of AI. However, the extent to which AI can contribute to enhancing export prices has not been fully substantiated, primarily due to the varying resource endowments and market positioning of these enterprises. The majority of non-state-owned enterprises are small and medium-sized in scale, with limited financial strength, which makes it difficult for them to afford the high investment required for full-process AI implementation. The primary focus of the company has been on basic links, such as replacing human workers with machines. However, this has not yet resulted in the formation of a competitive advantage that is sufficiently differentiated. Meanwhile, in the market sectors where non-state-owned enterprises operate, there is often a high level of competition between similar companies. Despite achieving cost savings through AI, companies often find themselves compelled to convert cost dividends into price advantages due to market competition pressures, rather than retaining them as price bonuses.

5.4.2 Heterogeneity of export destination countries

The classification of export destination countries is critical to understanding how AI influences the export price markup of enterprises. Marked differences across countries including in market demand characteristics, trade policy frameworks, digital infrastructure development, competitive intensity, and consumer preferences lead to variations in AI’s effect on firms’ export price markup. Drawing on the World Bank’s criteria for classifying developed and developing countries, this paper examines AI’s impact on the price markup of enterprises that export to these two types of destinations. As presented in columns (3)-(4) of Table 6, the regression results show that AI exerts a significant impact on the export price markup of enterprises selling to developed countries. However, there is no significant impact on the price markup for enterprises exporting to developing countries. Specifically, developed countries have well-developed digital infrastructure, which can support the implementation of AI technology. Enterprises can accurately capture the high demands of consumers in developed countries for product quality and functionality through cross-border data analysis driven by AI, achieve customized production of products with the help of intelligent production systems, and enhance international recognition by relying on brand marketing tools empowered by AI. These measures can effectively enhance the non-price competitiveness of products and thus enable the company to achieve a higher pricing space. In addition, the trade policies and compliance systems of developed countries are more conducive to the role of AI in supply chain traceability, adaptation to international standards and other links, further enhancing the effect of price markup. In contrast, the digital infrastructure in developing countries is relatively weak, and in some regions, it is difficult to fully embrace the application value of AI technology. Meanwhile, consumers in developing countries are highly sensitive to prices, and market demand is more inclined towards cost-effective products. Despite the fact that businesses may achieve cost optimisation through the implementation of AI, they frequently encounter challenges in maintaining market share through the use of a low-price strategy. Moreover, they often experience difficulties in converting technological advancements into price increases.

5.4.3 Heterogeneity of firm productivity

To more accurately clarify how AI affects the export price markup of enterprises, this paper classifies samples according to enterprise’ total factor productivity (TFP) levels, conducts heterogeneity analysis, and in-depth explores the differentiated mechanism underlying AI’s impact on price markup. Specifically, enterprises are divided into two groups: the low-TFP group (*tfp_l*) and the high-TFP group (*tfp_h*). The grouping criterion is whether an enterprise's TFP exceeds the median TFP of its respective HS2 digit industry. As shown in columns (1) and (2) of Table 7, the results indicate that AI significantly increases the price markup of enterprises in the high-TFP group, while it exerts a significant negative impact on the price markup of enterprises in the low-TFP group.

High-productivity enterprises have greater financial resources, technological reserves and human resources. They can also fully leverage the application value of AI. Investing in intelligent production equipment and industrial Internet systems can optimise manufacturing processes, enhance product quality and production efficiency. It can also rely on AI and big data analysis to strengthen brand building and cross-border precise marketing, and further expand the pricing space by leveraging its existing international market influence. Meanwhile, high-productivity enterprises have stronger innovation capabilities and can leverage AI to assist in the research and development of high-value-added products, better adapting to the diversified demands of the international market and further supporting the increase in price markups. While low-productivity enterprises may experience marginal improvements in operational efficiency through the integration of AI, they face challenges due to their weak technical foundations and limited resources. This hinders their ability to fully incorporate AI into their processes. In the context of intense international market competition, such enterprises may find themselves in a position of 'low-cost competition'. Despite the potential cost reductions enabled by AI, companies often find themselves compelled to decrease their prices in order to maintain their market share, owing to the absence of any significant competitive advantages. This can result in the suppression of price markup, and the full benefits of AI may not be realised.

5.4.4 Heterogeneity of firms with different competitive strategies

Export enterprises primarily engage in international market competition through two strategies: price competition and quality competition. When there is a positive relationship between price and sales, the quality competition strategy is adopted; otherwise, the cost competition strategy is adopted.Enterprises that adopt the price competition strategy usually formulate low-price plans with cost control as the core. Enterprises that adopt a quality competition strategy focus on upgrading product quality, innovating functions and optimising services. This paper identifies enterprise competitive strategies by referring to the method of Eckel *et al.,* [45]. The regression results in columns (3) and (4) of Table 7 demonstrate that AI exerts an inhibitory effect on the price markup of export enterprises adopting price competition strategies, while exhibiting a significant promoting effect on the price markup of export enterprises adopting quality competition strategies. Specifically, AI has significantly enhanced the efficiency of market information circulation and the response speed of enterprises. Enterprises that engage in price competition can use AI to monitor the pricing of competing products and fluctuations in market demand in real time. While they are able to adapt their prices rapidly in response to competitive pressures, this can also lead to price wars within the industry, forcing enterprises to continuously reduce price markups in order to maintain customer loyalty. For enterprises that adopt quality competition, AI can help increase price markup in two ways: On the one hand, AI-driven user profiling and demand analysis tools can accurately identify the quality and functionality requirements of overseas consumers, providing valuable insights for product innovation. Conversely, the implementation of AI quality inspection systems and intelligent production processes is instrumental in ensuring the consistency and reliability of product quality. Coupled with cross-border brand marketing empowered by AI, it further strengthens the non-price competitiveness of products, helps enterprises strive for higher pricing in the international market, and ultimately promotes the increase of price markup.

Table 7
Results of Heterogeneity Tests by Firm Productivity and Competitive Strategy

	Firm Productivity		Corporate Competitive Strategy	
	High Productivity (1)	Low Productivity (2)	Price Competition Strategy (3)	Quality Competition Strategy (4)
*AI*post*	0.0536**	-0.0869***	-0.0351**	0.2210***
	(0.0246)	(0.0016)	(0.0147)	(0.0048)
Controls	YES	YES	YES	YES
cons	-0.4764***	-0.0101***	0.2951***	0.3257***
	(0.0177)	(0.0039)	(0.0074)	(0.0150)
Firm–Product Fixed Effects	YES	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES	YES
R^2	0.4624	0.4262	0.2362	0.7573
N	3473	3387	3013	3847

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

6. Mechanism testing

6.1 Modelling

To examine the functioning mechanisms of positive spillover and negative competition in the context of AI , according to the suggestion of the test of intermediary effect by Jiang [46], this paper selects the intermediary variables that have direct theoretical correlation with the cost markup of the firms or are in line with the empirical common sense, and focuses the analyses on the causality identification of AI on the intermediary variables. The specific model is constructed as follows:

$$T_{fkjt} = \alpha + \beta_1 AI_{ft} * post_{ft} + \gamma \sum Control_{kjt} + \delta_{fk} + \delta_{jk} + \delta_{fj} + \delta_{kt} + \varepsilon_{fkjt} \tag{18}$$

In Eq. (18), T_{fkjt} denotes the mediating variable, and coefficient β_1 represents the effect of firms' AI application on the mediating variable; the other variables are defined as in the benchmark model.

6.2 Measurement of mediating variables

Productivity-enhancing effect ($production\_eff_{ft}$). This paper employs the Levinsohn and Petrin (LP) method to estimate the total factor productivity (TFP) of agribusinesses. Following the approach of James *et al.*, [47], we specify a Cobb–Douglas production function for measuring agribusiness TFP, which is formulated as follows:

$$lnY_{ft} = \beta_0 + \beta_1 lnK_{ft} + \beta_1 lnL_{ft} + \beta_1 lnM_{ft} + \varepsilon_{ft} \tag{19}$$

Among them, f represents the enterprise, t represents the year, Y_{ft} is the income of the enterprise, K_{ft} is the net fixed assets of the enterprise, L_{ft} is the number of employees of the enterprise, and L_{ft} is the intermediate inputs, which is measured by the cash paid by the enterprise for purchasing commodities and accepting labour services. Operating income is deflated using the factory price index of the region where the enterprise is located, while net fixed assets are deflated using the fixed-asset investment price index. The residuals are then computed to measure firm-level total factor productivity, denoted as $production\_eff_{ft}$.

Technology innovation effect ($tech\_inn_{ft}$). In order to reflect the quality level of enterprise green innovation more comprehensively and objectively, this paper adopts a comprehensive indicator system for measurement, and comprehensively selects three first-level indicators and eight second-level indicators of innovation input, innovation results and innovation performance to construct the innovation evaluation indicator system (Table 8). All the above indicators are positive indicators, meaning that higher values correspond to higher levels of firm innovation. In this paper, we use the entropy method to calculate the weight of each indicator, with the calculation basis being the degree of correlation between the indicators, thereby conducting an objective evaluation and achieving a scientific measurement of innovation levels.

Table 8
Construction of enterprise innovation quality indicator system

Primary	Secondary indicator	Content
Innovation input	Innovative human resource investment	Number of technical personnel
9	Innovation financial input	Internal expenditure of enterprise R&D funds
Innovation achievement	Exploratory innovation output	The sum of the number of utility model and design patent applications is taken as the natural logarithm
	Exploitative innovation output	Number of invention patent applications
	Enterprise economic performance	The proportion of PBIT of total operating revenue
Innovation performance	Innovation output scale	Product sales revenue
	Innovation competitiveness	Export technical complexity
	Innovation efficiency	Sum of innovation R&D efficiency and innovation transformation efficiency

Competition-intensifying effect ($barrier\_dec_{fht}$). The Herfindahl-Hirschman Index (*HHI*) was used to measure the degree of industrial agglomeration. Agglomeration index HHI_{ht} of h Industry (HS 4-digit code) in the year t is calculated as:

$$HHI_{ht} = \sum_{f=1}^{n_{ht}} S_{hft}^2\,, \quad S_{hjt} = \frac{X_{hft}}{\sum_{f=1}^{n_{ht}} X_{hft}} \tag{20}$$

In Eq. (20), X_{hft} represents the export value of the f enterprise in the h industry in the t year, n_{ht} represents the number of enterprises in the h industry in the t year, and S_{hft} represents the proportion of the export value of the f enterprise in the h industry in the t year. $HHI_{ht} \in [\frac{1}{n_{ht}}, 1]$, the larger $\frac{1}{n_{ht}}$ is, the higher the degree of concentration of the industry h is.

Transparency-enhancing effect ($transparency_{ft}$). In this paper, we measure two dimensions of market transparency and firm costs. First, this paper adopts the opacity composite index proposed by Anderson *et al.,* [48] as a proxy variable for corporate transparency. This index offers a relatively robust measure of corporate information transparency, as it integrates multiple dimensions—encompassing both the internal dimension of disclosure quality and the external dimension of market oversight. Specifically, the opacity composite index consists of four individual proxy variables: trading volume, bid-ask spread, analyst coverage, and analyst forecast error. In this paper, each of these four proxy variables is first sorted into deciles; among them, firms with the highest opacity are assigned a value of 10, while those with the highest transparency are assigned a value of 1. These four rankings are first summed, and the total is then divided by 40 (the maximum possible total score) to generate an opacity index, which ranges from 0.1 to 1.0. Specifically, lower values of this index correspond to higher corporate transparency, while higher values indicate greater corporate opacity. Second, the logarithmic value of the firm's operating costs $lncost_{ft}$ and the logarithmic value of the maintenance investment $lninvest_{ft}$ were used as cost variables for exporters.

6.2 Intermediary mechanism test

6.2.1 Positive mechanisms: efficiency improvement and technological innovation effects

The test results regarding AI's efficiency effect on the export price markup of enterprises are presented in column (1) of Table 9. Among these results, the coefficient of the AI variable is significantly positive. This empirical finding verifies Hypothesis 1: specifically, export enterprises can significantly enhance their production efficiency through AI application, which in turn drives an increase in their price markup. In the production process, AI-driven industrial robots and intelligent assembly lines can replace human labour to complete high-precision and high-repetition tasks, control errors, and ensure 24-hour operation to improve efficiency. In the operation stage, the AI supply chain management system integrates logistics information, dynamically adjusts plans to reduce inventory and logistics losses, and the intelligent cost accounting tool precisely breaks down costs, helping enterprises find areas for optimisation. The efficiency improvement and cost reduction effect of AI can help enterprises to increase profits, enhance the flexibility of international pricing, and ultimately drive up price markups.

The results of the test of the effect of technological innovation, as represented by AI, on the price markup of export enterprises are shown in column (2) of Table 9. The regression results indicate a significant positive coefficient for AI, thereby supporting Hypothesis 2. In terms of technological innovation, the use of AI-assisted virtual simulation, parameter optimisation and other R&D tools can reduce the cycle time and cost of trial and error, helping enterprises to develop products for niche markets (such as low-carbon products for Europe and durable products for Southeast Asia), and increase added value and competitiveness with unique advantages. In terms of operational technology innovation, the AI-driven production quality control system is able to monitor parameters and identify defects in real time, ensuring the consistency and high standards of export products. The AI supply chain traceability system can track data throughout the entire process, enhancing the trust of overseas consumers.

6.2.2 Negative mechanisms: market competition and information transparency effects

The regression results in Column (3) show that the coefficient of AI on market competition is significantly negative. This empirical finding supports Hypothesis 3, which posits that AI adoption by export enterprises strengthens market competition, thereby reducing their price markup. The widespread adoption of AI has a number of key benefits for the industry. It accelerates the diffusion of technology, lowers market entry barriers for new enterprises, and thereby significantly increases the number of market competitors. Notably, AI technology has also exerted a notable impact on two key aspects: the efficiency of market information dissemination and enterprises' market response speed. By leveraging intelligent data analysis tools, enterprises can access real-time insights into global market demand, competitor pricing strategies and shifts in consumer preferences. Concurrently, they must also contend with the rapid strategic adjustments of competitors utilising analogous technologies. In the current market environment, characterised by information transparency and accelerated response, competition within the industry has increased significantly. The market competition pressure intensified by AI has forced enterprises to balance the competing imperatives of maintaining market share and achieving profit targets, which has resulted in a significant reduction in the price markups of export enterprises.

The coefficient of AI in column (4) is significantly negative, while that in column (5) is significantly positive. This result indicates two key effects of enterprise AI application: first, it exerts a significantly positive impact on improving market transparency; second, it has a significantly negative effect on alleviating enterprises' own cost pressure. Together, these findings strongly support Hypothesis 4. In terms of market transparency, the AI-enabled information aggregation platform allows global customers and middlemen to quickly obtain product prices, specification parameters, delivery cycles and quality evaluations of different export enterprises, completely breaking the information asymmetry pattern in traditional markets. Sellers are no longer able to rely on information asymmetry to maintain high pricing, and their bargaining power has been significantly suppressed. They have no option but to reduce the price markup to match the fair pricing level of the market. Despite enterprises achieving operational efficiency and cost reductions through the implementation of AI, the weakened bargaining power resulting from increased market transparency, in conjunction with price competition due to oversupply, has collectively led to a decline in the price markup rate. Consequently, the actual profitability of enterprises has not improved simultaneously, and they may even fall into a 'low-profit operation' predicament due to price wars.

Table 9
Results of the mediation effect test

	Efficiency improvement effect	Technological innovation effect	Market competition effect	Information transparency effect	
	(1)	(2)	(3)	(4)	(5)
*AI*post*	0.0176***	0.1209***	0.1546***	-0.0323***	0.0316***
	(0.0048)	(0.0071)	(0.0217)	(0.0061)	(0.0026)
Controls	YES	YES	YES	YES	YES
cons	-0.0028	-0.7243***	-0.1266***	0.0059**	0.0011***
	(0.0086)	(0.0912)	(0.0359)	(0.0024)	(0.0003)
Firm–Product Fixed Effects	YES	YES	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES	YES	YES
R^2	0.0785	0.0374	0.1367	0.2712	0.1422
N	6860	6860	6860	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

7. Further discussion

In the heterogeneity analysis, it is found that AI exerts a positive effect on the price markup of enterprises adopting quality-competitive strategies, while it has a negative effect on those pursuing price-competitive strategies trapping the latter in a 'low markup rate trap'. This study further explores whether AI can transform the competitive strategy of enterprises to realise its effect on price markup. This study argues that when price and sales are positively related within a firm, it adopts a quality-based competitive strategy, and vice versa for a cost-based competitive strategy. Therefore, we define a competitive strategy shift variable ($strategy\_trans_{ft}$) with the following assignment rules: it takes a value of 1 if a firm's competitive strategy shifts from price competition to quality competition in the current year; a value of -1 if the strategy shifts from quality competition to price competition; and a value of 0 if the strategy remains unchanged compared to the previous year. As shown in column (1) of Table 10, the coefficient of the interaction term *AI*post* is significantly positive. This result indicates that AI application helps enterprises shift their competitive strategy from price competition to quality competition.

AI has significantly shifted firms' competitive strategies away from traditional price competition toward quality competition. Instead of simply cutting prices to attract customers, companies can now use data analysis to optimise product design, improve productivity and enhance customer experience. In this way, companies can offer higher quality products and services to meet rising consumer expectations and to differentiate themselves from the competition. As a result, quality has become the centre of competition, rather than just a price factor, driving companies to build stronger brand advantages in the marketplace.

In addition, the negative effect of AI on firms' price markups, confirmed in the previous part of the mechanism study, provides insights into resource allocation efficiency. A price markup greater than 1 implies that prices are inconsistent with marginal costs, which itself has distorting implications [9]. Therefore, does a decrease in a firm's price markup correspond to improved resource allocation in its industry? To address this question, this study uses two key indicators to examine the relationship between AI application and the degree of resource mismatch in the HS2 digit code industry to which the firm belongs: first, the dispersion of firm-level total factor productivity (TFP) adjusted by the firm's price markup ($TFPQ_{ft}$); second, the dispersion of firm-level price markup (*markup_sd*). The estimation results are presented in Table 10. The coefficients of the interaction term *AI*post* in columns (2)–(3) are both significantly negative, which indicates that AI application significantly enhances the efficiency of resource allocation in the HS2 digit code industry where the firm operates.

Table 10
Results of testing the AI of enterprises with competitive strategy shift and optimal resource allocation

	strategy_trans	*TFPQ*	*markup_sd*
	(1)	(2)	(3)
*AI*post*	0.2596^{***}	-0.9911^{***}	-0.8958^{***}
	(0.0056)	(0.0502)	(0.0506)
Controls	YES	YES	YES
cons	-1.4899^{***}	0.1472^{***}	0.1573^{***}
	(0.0601)	(0.0247)	(5.67)
Firm–Product Fixed Effects	YES	YES	YES
Destination–Product Fixed Effects	YES	YES	YES
Firm–Destination Country Fixed Effects	YES	YES	YES
Product–Year Fixed Effects	YES	YES	YES
R^2	0.2351	0.0886	0.1546
N	6860	6860	6860

Note: *** , ** and * indicate significance levels of 1%, 5% and 10%, respectively, with standard error in parentheses.

8. Conclusions and policy implication

8.1 Conclusion

The rapid integration of AI technology across industries has driven a marked surge in its adoption among export enterprises. This paper systematically investigates the impact and underlying mechanisms of AI on the export price markup of enterprises. To achieve this, we integrate data from China's Customs Database and the dataset of manufacturing listed companies on the Shanghai and Shenzhen A-share markets spanning 2007 to 2016. This integrated dataset is further combined with AI indicators, which are constructed by extracting and analyzing the annual report texts of listed companies using large language models.

The research findings reveal that AI adoption contributes to an increase in the export price markup of enterprises. Notably, the ‘intelligent empowerment’ model exerts a more pronounced promotional effect on price markup compared to the ‘machine replacing human’ model. Mechanism analysis demonstrates that AI’s impact on export price markup is dual-sided: it generates positive effects through efficiency enhancement and technological innovation, while simultaneously exerting negative effects via intensified market competition and improved information transparency.

Heterogeneity analysis indicates that AI delivers a stronger positive boost to the export price markup of specific enterprise groups, including state-owned enterprises, high-productivity enterprises, enterprises adopting quality-based competitive strategies, and those exporting to developed countries. Further research also finds that AI reduces the dispersion of enterprise-level price markups and significantly enhances the efficiency of resource allocation within industries.

8.2 Policy implication

Firstly, it is recommended that export enterprises enhance their AI application capabilities and optimise technology application models, with efforts needed in two key aspects. Focus on AI infrastructure construction: increase investment in core facilities like intelligent computing power platforms and industrial Internet, provide support for AI application in production, supply chain and other links, and ensure data processing and decision-making efficiency in cross-border business. Promote the integration of AI with the entire operational process: introduce intelligent production systems to reduce costs, use cross-border intelligent marketing tools to analyse international market demands, rely on ‘intelligent empowerment’ to strengthen non-price advantages, reduce over-reliance on ‘machine replacing human’, and efficiently convert AI dividends into price enhancements.

Secondly, the government should refine the policy support system to facilitate AI application among export enterprises. To provide targeted and necessary support, it is essential for the government to establish a comprehensive framework encompassing three core dimensions: financial support, policy guarantees, and infrastructure development. Specifically, a dedicated fund for AI application in export enterprises should be set up, with its focus directed toward supporting small and medium-sized export enterprises (SMEs) in adopting AI technologies and procuring related equipment. This targeted support addresses the common challenges faced by SMEs such as limited capital and technical capacity—in accessing AI, thereby narrowing the ‘digital gap’ between large enterprises and SMEs in the export sector. It is recommended that subsidies be provided to enterprises that carry out demonstration projects such as ‘AI + Cross-border Supply Chain’ and ‘AI + Product Innovation’, and that the threshold for technology application be lowered. Optimise tax incentive policies, implement additional tax deductions for enterprises’ AI research and development investment, and offer export tax rebates to enterprises that enhance the added value of exports through AI technology to stimulate investment. In order to enhance the development of cross-border digital infrastructure, it is essential to promote the expansion of international communication networks and the establishment of cross-border data security circulation mechanisms. Concurrently, it is necessary to establish a public AI service platform to provide low-cost basic services for enterprises and alleviate the resource constraints of small and medium-sized enterprises.

Thirdly, industry associations should assume responsibility for collaborative governance in order to regulate the market competition order that has been engendered by AI. It is imperative that industry associations concentrate on the dual objectives of promoting competition and preventing chaos. On the one hand, formulating industry-specific norms and competition guidelines for AI application in exports is imperative to avoid disorderly competition. On the other hand, it is essential to clearly define compliance boundaries for AI use in this sector, covering areas like data security and algorithm transparency. Furthermore, the establishment of an industry price monitoring and early warning mechanism to promptly intervene in vicious price competition and maintain a fair market environment is crucial. Conversely, the establishment of a platform for the dissemination of AI resources is recommended, with the aim of integrating high-quality AI technology resources within the industry. The provision of services such as AI application training and technical consultation for small and medium-sized enterprises is also suggested, with the objective of enhancing their AI application capabilities and averting excessive concentration of market share due to technological gaps. Concurrently, the organisation of regular industry exchange activities is imperative to promote the sharing of AI technology experience among enterprises. The objective is to guide enterprises in shifting from price competition to value competition empowered by AI, thereby reducing resource waste and promoting the coordinated improvement of price increase and resource allocation efficiency throughout the industry through AI technology.

8.3 Future direction

Future research can be expanded in two key directions: First, it is necessary to refine the classification of AI technologies such as the ‘intelligent empowerment’ model and ‘machine replacing human’ model to explore the heterogeneous impacts of different AI technologies on the price markup of export enterprises, as well as their specific functional paths in links like production operations and supply chain management. Second, it is essential to leverage data with a longer time span to analyze the long-term dynamic effects of AI on enterprise price markup. This will further enable observation of the sustainability of its impact and potential shifts in its mechanism of action.

Appendix I

Table A1
List of keywords related to AI

Type	Dimension	High-Frequency Keywords	Brief Description of Core Characteristics
Machine Replacement (Automation-Oriented)	Production & Manufacturing Scenarios	Industrial robots, automated production lines, precision welding robots, intelligent stamping equipment, automated testing equipment, automatic assembly lines, automated painting, collaborative robots, flexible automation, autonomous driving (industrial)	Focuses on core factory production links. Replaces manual labor with industrial robots and automated equipment to perform repetitive physical tasks such as welding and stamping. Collaborative robots and industrial autonomous driving adapt to scenarios like in-plant material transfer, balancing production precision and flexible adjustment needs, and aligning with enterprises’ practical demands for cost reduction and efficiency improvement.
	Warehousing & Logistics Scenarios	AGV (Automated Guided Vehicle), intelligent automated warehouse (AS/RS), automatic sorters, unmanned delivery vehicles, autonomous driving (freight), human-machine collaboration, intelligent collaboration systems	Covers key logistics links including warehousing, sorting, and short-distance transportation. Uses equipment like AGVs and automated warehouses to realize automatic cargo handling and storage. The human-machine collaboration model adapts to small-batch, multi-category order requirements, reducing labor dependence in logistics and improving circulation efficiency and error rate control.

Table A1
Continued

Type	Dimension	High-Frequency Keywords	Brief Description of Core Characteristics
Machine Replacement (Automation-Oriented)	Operation & Control Scenarios	RPA (Robotic Process Automation), process automation, intelligent sensors, smart home control, edge intelligence, Edge AI, end-side AI	Targets procedural operations (e.g., enterprise finance, administration) and production equipment on/off control. Replaces manual repetitive operations with RPA and end-side intelligence technologies. Combines intelligent sensors to collect real-time equipment status, reducing manual operation errors, enhancing the real-time performance of production control, and adapting to the lightweight automation needs of small and medium-sized enterprises.
Intelligent Empowerment(Intelligence-Oriented)	Data Processing & Analysis	Machine learning, deep learning, big data analysis, data mining, computer vision, speech recognition, NLP (Natural Language Processing), generative AI (intelligent customer service/marketing), AIGC, industry-specific large models (vertical fields), large model inference, big data, massive data, heterogeneous data, data integration, data modeling, data visualization, privacy computing, knowledge graphs, knowledge representation, pattern recognition, feature extraction, feature identification, SVM (Support Vector Machine), neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), LSTM (Long Short-Term Memory), reinforcement learning, deep neural	Takes enterprise operational and production data as the core. Processes multi-source data through technologies like machine learning and big data analysis. Generative AI and vertical-field large models focus on practical scenarios such as intelligent customer service responses and marketing copy generation. Extracts data value to support business decisions, balancing data security (privacy computing) and analysis efficiency, and meeting enterprises' basic needs for data-driven transformation.
Digital Efficiency Improvement	Risk Management & Decision-Making	Intelligent risk control, predictive maintenance, intelligent prediction algorithms, real-time data monitoring platforms, knowledge graphs, blockchain (supply chain traceability), smart contracts, distributed ledgers, big data risk control, intelligent supervision	Combines real-time data monitoring and algorithmic models to realize fault prediction for production equipment and supply chain risk identification. Blockchain technology focuses on supply chain traceability to ensure the credibility of material sources. Intelligent risk control adapts to compliance management needs in finance and manufacturing, improving the accuracy of enterprise risk early warning and management.
	Full-Chain Collaborative Management	Industrial Internet platforms, digital twins, intelligent scheduling systems, cross-entity collaboration systems, intelligent inventory management systems, operational optimization, AI-aided R&D, virtual simulation testing, cloud computing, public cloud, private cloud, hybrid cloud, IaaS, PaaS, SaaS, intelligent computing, distributed computing	Breaks down internal and external enterprise data silos through Industrial Internet platforms. Cloud computing provides flexible computing power support. AI-aided R&D and virtual simulation testing adapt to manufacturing process optimization and product testing scenarios. Intelligent scheduling and inventory management systems realize supply chain resource collaboration, reducing communication costs and inventory pressure across the entire chain.

Table A1
Continued

Type	Dimension	High-Frequency Keywords	Brief Description of Core Characteristics
Digital Efficiency Improvement		Scenario-Based Application Extension	Intelligent customer service, virtual service assistants, AI dialogue systems, intelligent patent analysis, intelligent recommendation systems, AI marketing algorithms, AI-based user profiling, mobile payments, APPs, short videos, live-streaming e-commerce, intelligent education, smart government services, smart banking, smart finance, intelligent insurance, intelligent retail, intelligent healthcare (medical imaging diagnosis), intelligent transportation, smart homes, smart agriculture, intelligent environmental protection, intelligent investment advisory, human-machine dialogue, AI products, business intelligence, intelligent elderly care, Q&A systems, machine translation, speech synthesis, voice interaction, biometrics, voiceprint recognition, face recognition, intelligent agents, intelligent search
Neutral/Basic Technologies(Context-Determined)	Data Transmission & Storage	5G, cloud computing, edge computing, big data (storage layer), object storage, analytical databases, time-series databases, cloud storage, cloud servers, EVS (Elastic Volume Service), big data platforms, big data processing, big data management, big data operations	Serves as the underlying support for machine replacement and intelligent empowerment. 5G ensures high-speed connectivity between equipment and systems. Cloud computing and cloud storage provide data storage and flexible computing power. Various databases adapt to enterprises' needs for managing structured and time-series data. Edge computing enhances the real-time performance of production-side data processing, solving basic enterprise pain points in data transmission and storage.
	Intelligent Computing Support	Artificial intelligence (basic algorithm layer), intelligent chips, AI algorithms (equipment action optimization/decision analysis), cognitive computing, augmented intelligence, machine learning frameworks, AI chips, deep neural networks	Provides core computing capabilities for AI applications. AI algorithms adapt to practical needs such as production equipment action optimization and business decision analysis. Intelligent chips and machine learning frameworks improve computing efficiency, reducing hardware costs and technical thresholds for enterprises to deploy AI technologies, and supporting the stable operation of various AI applications.
	Virtual-Physical Interaction Support	IoT (Internet of Things), AR (Augmented Reality), VR (Virtual Reality), intelligent voice (interaction layer), RFID, sensors, micro-nano sensors, infrared sensors, laser scanners, barcodes, Industrial IoT, embedded systems, wearable devices, intelligent sensors, AR (industrial design), VR (virtual assembly)	Enables physical object status perception and data collection through devices like sensors and RFID. Industrial IoT adapts to in-plant equipment connectivity needs. AR/VR focuses on industrial design and virtual assembly scenarios, assisting engineers in optimizing design schemes and reducing physical trial-and-error costs. Intelligent voice provides a convenient human-machine interaction method, supporting front-end perception and interaction needs.

Author Contributions

Conceptualization, W.W.Q.; Methodology, W.W.Q.; Validation, Z.S.L., W.W.Q.; Investigation, W.W.Q.; Writing-original draft preparation, Z.S.L., W.W.Q.; Writing-review and editing, Z.S.L., W.W.Q. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability Statement

Data will be available on reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

References

[1] Sheng, D., & Liu, Z. Q. (2017). RMB Exchange Rate, Processing Trade and Markups of Chinese Firms. *World Economy, 40*(1), 3–24. https://doi.org/10.19985/j.cnki.cassjwe.2017.08.005

[2] An, G., & Wang, J. (2023). Local Market Size and Firm Price Markup——Micro Evidence from Chinese Enterprises. *Journal of International Trade, 8*, 88–105. https://doi.org/10.13510/j.cnki.jit.2023.08.006

[3] Popescu, A. I. (2024). The Evolution of On-demand Platforms: Conceptual Framework, Regulatory Challenges, and Policy Implications in the Digital Economy. *International Journal of Economic Sciences, 13*(2), 55-86. https://doi.org/10.52950/ES.2024.13.2.004

[4] Alkhudary, R., Queiroz, M. M., & Féniès, P. (2024). Mitigating the Risk of Specific Supply Chain Disruptions Through Blockchain Technology. *Supply Chain Forum: An International Journal, 25*(1), 1–11. https://doi.org/10.1080/16258312.2022.2090273

[5] Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, Firm Growth, and Product Innovation. *Journal of Financial Economics, 151*, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

[6] Lerner, A. P. (1934). The Concept of Monopoly and the Measurement of Monopoly Power. *Review of Economic Studies, 1*, 157–175. https://doi.org/10.2307/2967480

[7] Domowitz, I., Hubbard, R. G., & Petersen, B. C. (1986). Business Cycles and the Relationship between Concentration and Price-cost Margins. *Rand Journal of Economics, 17*(1), 1–17. https://doi.org/10.2307/2555624

[8] Siotis, G. (2003). Competitive pressure and Economic Integration: An Illustration from Spain, 1983–1996. *International Journal of Industrial Organization, 21*, 1435–1459. https://doi.org/10.1016/S0167-7187(03)00051-1

[9] Edmond, C., Midrigan, V., & Xu, D. Y. (2015). Competition, Markups, and the Gains from International Trade. *American Economic Review, 105*(10), 3183–3221. https://doi.org/10.1257/aer.20120549

[10] De Loecker, J., & Warzynski, F. (2012). Markups and Firm–Level Export Status. *The American Economic Review, 102*(6), 2437–2471. https://doi.org/10.1257/aer.102.6.2437

[11] Bai, P. W., & Yu, L. (2021). Digital Economy Development and Firms' Markup: Theoretical Mechanisms and Empirical Facts. *China Industrial Economy, 11*, 59–77. https://doi.org/10.19581/j.cnki.ciejournal.2021.11.003

[12] Fang, P. P., & Liao, H. (2022). Intermediate Input Import Competition, Supply Chain Linkages and Markup of Supply Enterprise. *World Economy Study, 10*, 55–71+136. https://doi.org/10.13516/j.cnki.wes.2022.10.005

[13] Myers, M. B., Cavusgil, S. T., & Diamantopoulos, A. (2002). Antecedents and Actions of Export Pricing Strategy: A Conceptual Framework and Research Propositions. *European Journal of Marketing, 36*, 159–188. https://doi.org/10.1108/03090560210412746

[14] Indounas, K., & Avlonitis, G. J. (2009). Pricing Objectives and Their Antecedents in the Services Sector. *Journal of Service Management, 20*, 342–374. https://doi.org/10.1108/09564230910964426

[15] Tan, Q., & Sousa, C. M. P. (2015). Leveraging Marketing Capabilities into Competitive Advantage and Export Performance. *International Marketing Review, 32*(1), 78-102. https://doi.org/10.1108/IMR-12-2013-0279

[16] Huang, K. Y., Li, Z. F., Pan, N. P., & Ni, J. W. (2023). Enterprise Digital Transformation and Share of Labor Income. *Economic Review, 2*, 15–30. https://doi.org/10.19361/j.er.2023.02.02
[17] Freund, C. L., & Weinhold, D. (2004). The Effect of the Internet on International Trade. *Journal of International Economics, 62*(1), 171–189. https://doi.org/10.1016/S0022-1996(03)00059-X
[18] Acemoglu, D., & Restrepo, P. (2020). The Wrong Kind of AI? Artificial Intelligence and the Future of Labour Demand. *Cambridge Journal of Regions, Economy and Society, 13*(1), 25–35. https://doi.org/10.1093/cjres/rsz022
[19] Goldfarb, A., & Trefler, D. (2018). AI and International Trade. *NBER*, 24254. https://doi.org/10.3386/w24254
[20] Maity, S., & Majumder, A. (2025). A Comparative Study on the Financial Inclusion Status of G20 Countries. *Journal of Decision Analytics and Intelligent Computing, 5*(1), 14–24. https://doi.org/10.31181/jdaic10015022025m
[21] Alguacil, M., Turco, A. L., & Martínez-Zarzoso, I. (2022). Robot Adoption and Export Performance: Firm-level Evidence from Spain. *Economic Modelling, 114*, 105912. https://doi.org/10.1016/j.econmod.2022.105912
[22] Brynjolfsson, E., Hui, X., & Liu, M. (2019). Does Machine Translation Affect International Trade? Evidence from a Large Digital Platform. *Management Science, 65*(12), 5449–5460. https://doi.org/10.1287/mnsc.2019.3388
[23] DeStefano, T., & Timmis, J. (2024). Robots and Export Quality. *Journal of Development Economics, 168*, 103248. https://doi.org/10.1016/j.jdeveco.2023.103248
[24] Lyu, Y., Zhang, H. T., & Gao, K. L. (2024). On Extension of China's Industrial Chain in the Era of Artificial Intelligence: Evidence from Firms' Imports of Industrial Intelligent Equipment. *China Industrial Economics, 1*, 56-74. https://doi.org/10.19581/j.cnki.ciejournal.2024.01.004
[25] Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial Intelligence and Firm-level Productivity. *Journal of Economic Behavior & Organization, 211*, 188-205.
[26] Zhao, C. M., & Chu, T. T. (2024). Study on the Influence of Artificial Intelligence Application on the Technical Complexity of Export——Based on Chinese Industry Panel Data. 6, 58-66. https://doi.org/10.13580/j.cnki.fstc.2024.06.003
[27] Melitz, M. J., & Ottaviano, G. I. P. (2008). Market Size, Trade, and Productivity. *Review of Economic Studies, 75*, 295–316. https://doi.org/10.1111/j.1467-937X.2007.00463.x
[28] Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting and Social Change, 182*, 121785. https://doi.org/10.1016/j.techfore.2022.121785
[29] Cosar, A. K., & Guner, N., & Tybout, J. (2016). Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy. *American Economic Review, 106*(3), 625–663. https://doi.org/10.1257/aer.20110457
[30] Niu, Z. H., Jin, H., & Li, X. Z. (2025). The Impact of Smart Manufacturing on Firm Markup. *Journal of Guangdong University of Finance & Economics, 9*, 1–13. https://doi.org/10.20209/j.gcxb.441711.20250926.001
[31] Xia, T., Zhou, J. H., & Sun, J. W. (2024). Development of Digital Economy, Government Intervention, and Urban Economic Resilience. *China Soft Science, 5*, 111–121.
[32] Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*(1), 37-50. https://doi.org/10.1016/j.bushor.2019.09.003
[33] Parteka, A. & Kordalska, A. (2023). Artificial Intelligence and Productivity: Global Evidence from AI Patent and Bibliometric Data. *Technovation, 125*, 102764. https://doi.org/10.1016/j.technovation.2023.102764
[34] Autor, D., Dorn, D., Katz, L. F., & Patterson, C. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *Quarterly Journal of Economics, 135*(2), 645–709. https://doi.org/10.1093/qje/qjaa004
[35] Grashof, N. & Kopka, A. (2023). Artificial Intelligence and Radical Innovation: an Opportunity for All Companies?. *Small Business Economics, 61*(2), 771-797. https://doi.org/10.1007/s11187-022-00698-3
[36] Li, C. M., Xu, Y., & Zheng, H., et al. (2023). Artificial Intelligence, Resource Reallocation, and Corporate Innovation Efficiency: Evidence from China's Listed Companies. *Resources Policy, 81*, 103324. https://doi.org/10.1016/j.resourpol.2023.103324
[37] Healy, P. M., & Palepu, K. G. (2001). Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure literature. *Journal of Accounting and Economics, 31*(1), 405–440. https://doi.org/10.1016/S0165-4101(01)00018-0
[38] Ma, S. Z., Pu, F. Q., & Xiao, Z. H. (2024). The Flow and Value Creation of Agricultural Big Data: A Perspective Based on Supply—Demand Matching. *Issues in Agricultural Economy, 8*, 13–24. https://doi.org/10.13246/j.cnki.iae.2024.08.007
[39] Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?*. W.E. Upjohn Institute. https://www.jstor.org/stable/j.ctvh4zh1q
[40] Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review, 110*(8), 2586–2624. https://doi.org/10.1257/aer.20181047

[41] Yao, J. Q., Zhang, K. P., & Guo, L. P, et al. (2024). How Does Artificial Intelligence Improve Firm Productivity? Based on the Perspective of Labor Skill Structure Adjustment. *Management World, 40*(2), 101-116. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018

[42] Crinò, R., & Ogliari, L. (2017). Financial Imperfections, Product Quality, and International Trade. *Journal of International Economics, 104*, 63–84. https://doi.org/10.1016/j.jinteco.2016.10.005

[43] Beck, T. H. L., Levine, R., & Levkov, A. (2010). Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *Journal of Finance, 65*(5), 1637–1667. https://doi.org/10.1111/j.1540-6261.2010.01589.x

[44] Chetty, R. (2009). Is the Taxable Income Elasticity Sufficient to Calculate Deadweight Loss? The Implications of Evasion and Avoidance. *American Economic Journal: Economic Policy, 1*(2), 31–52. https://doi.org/10.1257/pol.1.2.31

[45] Eckel, C., Iacovone, L., Javorcik, B., & Neary, J. P. (2015). Multi–Product Firms at Home and Away: Cost–versus Quality–Based Competence. *Journal of International Economics, 95*(2), 216–232. https://doi.org/10.1016/j.jinteco.2014.12.012

[46] Jiang, T. (2022). Mediating Effects and Moderating Effects in Causal Inference. *China Industrial Economics, 5*, 100–120. https://doi.org/10.19581/j.cnki.ciejournal.2022.05.005

[47] James, L., & Amil, P. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies, 70*(2), 317–341. https://doi.org/10.1111/1467-937X.00246

[48] Anderson, R. C., Duru, A., & Reeb, D. M. (2009). Founders, Heirs, and Corporate Opacity in the United States. *Journal of Financial Economics, 92*(2), 205–222. https://doi.org/10.1016/j.jfineco.2008.04.006