



Article

Artificial Intelligence and China's Cross-Border E-Commerce Development: Threshold Effects and Transmission Mechanisms

Meina Zhao * and Lu Zhou

School of Economics and Business Administration, Heilongjiang University, Harbin 150080, China

* Correspondence: 2018056@hlju.edu.cn

Abstract

The integration of artificial intelligence and search technology is transforming traditional online shopping models, particularly cross-border e-commerce (CBEC), which involves complex customer multi-attribute decision-making with numerous considerations. This study systematically examines the influence of artificial intelligence on the high-quality advancement of CBEC and its underlying mechanisms using panel data from 30 Chinese provinces covering the period 2013–2023. The study found a significant positive correlation between artificial intelligence and cross-border e-commerce. This conclusion remains valid after a series of robustness tests (including removing the interference of pandemic-related data, substituting core explanatory variables, substituting the dependent variable, and lagging explanatory variables by one period). Mechanism analysis indicates that the positive impact of AI on the high-quality development of cross-border e-commerce is realized through improvements in logistics capabilities and the unlocking of consumer potential, with mediation effects accounting for 40.27% and 17.02%, respectively. Threshold model results show that the positive impact of AI on the high-quality development of cross-border e-commerce exhibits a single threshold effect based on the level of human capital; once human capital exceeds the threshold value, the coefficient further increases. Heterogeneity analysis reveals that AI has the most significant empowering effect on the development of cross-border e-commerce in the eastern regions; however, its impact on the central and western regions is relatively minor. It is worth noting that AI exerts its empowering effect more effectively in regions with high e-commerce procurement activity, whereas the relationship is not significant in regions with low activity.

Keywords: artificial intelligence; CBEC; service efficiency; human capital



Academic Editors: Ruiliang Yan,
Zhi Pei and Hua Pang

Received: 8 September 2026

Revised: 13 October 2026

Accepted: 14 October 2026

Published: 16 October 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\) license](#).

1. Introduction

Alongside economic restructuring and industrial upgrading, CBEC is emerging as a novel impetus for China's economic development, a novel avenue for digital transformation and enhancement, and a novel pillar of high-quality development. Furthermore, the growth of new trade models such as digital trade and green trade has accelerated significantly, while the implementation of the Regional Comprehensive Economic Partnership (RCEP) has created fresh opportunities for the deepening of regional cooperation and offers broad prospects for the development of CBEC [1].

However, China's transnational electronic commerce sector currently faces many challenges. For instance, previous research shows that the high-quality development of CBEC is hindered by inadequate implementation of fundamental digital technologies and the need to enhance the service capabilities of 'new digital infrastructure' [2]. It has been

argued that improper management during the development of ‘overseas warehouses’ can easily lead to stock overflow issues [3]. Scholars believe that platforms are highly similar, with regional characteristics not being sufficiently distinct [4]. Such issues highlight the need for the CBEC industry to adapt to the new era through new drivers, new technologies, new business models, and, most especially, through the utilization of artificial intelligence.

Amidst the swift advancement of artificial intelligence technologies, human society is accelerating its transition into the intelligent economy era, and the advancement of AI has become a crucial factor influencing national economic and social development. Indeed, digital information technologies, centered on the internet, big data, and cloud computing, have disrupted the traditional economic development model dominated by the industrial economy, spawning an entirely new techno-economic paradigm [5,6], and the ‘tool revolution’ and ‘decision-making revolution’ brought about by AI are driving profound industrial transformation [7]. For the CBEC sector, AI technologies, particularly generative AI, not only enable faster collection and aggregation of transaction data and the identification of user needs, thereby facilitating the precise matching of products with demand, but also help create new product forms, which has important implications for the high-quality development of China’s CBEC.

The current academic research on the influence of artificial intelligence on economic development primarily focuses on changes in employment, enhancing corporate innovation capabilities, accelerating the innovation process, building supply chain resilience, and the metamorphosis and enhancement of industrial frameworks. Firstly, the most notable feature of artificial intelligence is its ability to endow machinery with intelligence, enabling it to replace humans in performing specific tasks [8,9]. In this regard, it is indicated that AI technology can replace part of the workforce with intelligent machines, and thereby reduce enterprises’ production costs [10]. Secondly, it has been argued that AI, through multiple pathways including the acceleration of knowledge generation and technology spillovers, the enhancement of learning and absorption skills, and the augmentation of investment in research, development, and talent, can not only upgrade existing technologies but also shorten the innovation process [11,12]. Finally, the development of artificial intelligence has raised productivity levels and accelerated economic growth. Through deep integration with traditional manufacturing, it is driving the transformation of traditional production methods towards intelligent systems, thereby increasing effective demand for industrial development and ultimately improving industrial structure [13,14] whilst elevating the structural level of the modern service sector.

Regarding the role of artificial intelligence in CBEC, it is found that AI can enhance operational efficiency whilst improving the customer experience [15]. Research also indicates that AI can provide direct design and sales solutions for specific products; for instance, generative AI can efficiently produce cross-cultural design proposals, facilitating the international spread of paper-based cultural and artistic items [16].

In summary, whilst domestic and international scholars have extensively examined the impact of AI in the economic sphere, research gaps remain. There has been little research into the impact of artificial intelligence on the high-quality development of cross-border e-commerce, nor has there been any empirical analysis of its underlying mechanisms. Consequently, panel data from 30 Chinese provinces covering the period 2013–2023 are used to reveal the influence of AI on the high-quality development of CBEC. By constructing dual-mediation and single-threshold models, we empirically test the promotional role of AI in this area, the threshold effect of human capital levels, and the heterogeneous impacts across different regions with varying levels of e-commerce procurement activity.

2. Theoretical Examination and Research Hypotheses

2.1. *The Direct Impact of Artificial Intelligence on the High-Quality Development of CBEC*

With the deepening integration of global trade and the rapid development of CBEC, traditional CBEC logistics enterprises are facing unprecedented challenges such as information asymmetry, low operational efficiency, and high costs [17]. Artificial intelligence may be the solution. Through iterative learning and algorithm optimization, artificial intelligence can enhance system operational efficiency, drive innovation in cross-border e-commerce online marketing strategies, accurately identify customer needs, and improve the operational efficiency of logistics networks, thereby promoting the high-quality development of CBEC. In terms of optimizing resource allocation and reducing transaction costs, AI can leverage its learning capabilities to continuously generate new knowledge and iterate algorithms based on big data resources, thereby mitigating biases arising from human judgment [18]. Specifically, generative artificial intelligence lowers research and development trial-and-error costs through a “cloud-based trial-and-error” mechanism, replacing repetitive manual labor with automated content generation, refining the identification of consumer needs, and improving supply chain responsiveness via multimodal data analysis [19,20].

In 2026, scholars created a theoretical foundation for describing how artificial intelligence (AI) reshapes international business (IB) [21]. They argued that, for multinational enterprises, AI facilitates centralized control by enabling better integration and the real-time visibility of global operations while improving operational efficiency by supporting real-time coordination and reducing decision-making costs. For CBEC specifically, the development of cross-border e-commerce enterprises requires real-time awareness of global market conditions and real-time responses to orders, inventories, and customer demand. Thus, by deploying AI, cross-border e-commerce firms can integrate global operations, cut decision-making costs, and advance the high-quality development of cross-border e-commerce. This provides a theoretical basis for the argument that AI promotes cross-border e-commerce development.

AI also transforms how multinational corporations learn, innovate, develop resources and capabilities, and make cross-border decisions. It has been suggested that AI exerts impacts on international business through information processing, content creation, and autonomous action [21]. Furthermore, the growth of cross-border e-commerce demands that managers integrate global resources for market positioning, product selection, and digital influence, and AI adoption accelerates the efficiency of these processes, enabling personalized marketing strategies tailored to target markets. Moreover, the deployment of intelligent recommendation and intelligent review systems helps attract more target customers, while three-dimensional dynamic marketing technologies create new opportunities to build customized, immersive, and engaging shopping experiences [22]. Jointly driven by the above multi-layered mechanisms, artificial intelligence empowers every segment of CBEC operations and serves as a core driver for its high-quality development. Accordingly, the following research hypothesis is proposed:

Hypothesis 1. *Artificial intelligence can promote the high-quality development of CBEC.*

2.2. *Examination of the Mechanisms by Which Artificial Intelligence Propels the High-Quality Development of CBEC*

Artificial intelligence fuels the high-quality growth of CBEC via two core channels: logistics capacity advancement and consumer demand stimulation. In terms of the first channel, AI has sparked constant technological breakthroughs across industries and spawned innovative practical applications in numerous scenarios [23,24]. Previous research shows

that the integration of artificial intelligence and modern logistics greatly elevates the operational efficiency of conventional logistics systems, broadens service coverage, and creates favorable conditions for logistics firms to optimize scheduling arrangements [25,26].

When processing massive transport data, artificial intelligence strengthens logistics enterprises' capacity to collect and analyze information, guaranteeing data authenticity and an instant response. Such robust data infrastructure helps businesses improve their operational efficiency while tackling prevalent obstacles, including excessive dependence on manual work and barriers to internal information sharing [27–29]. Meanwhile, upgraded cognitive computing power and AI-enabled service model innovations support data-supported, flexible decision-making amid complex operations, while immersive virtual reality (VR) technology is reshaping the logic of traditional e-commerce [30], substantially increasing supply chain resilience and pushing it into a new transformative phase [31,32]. Furthermore, by adopting dynamic route planning, intelligent warehouse allocation, and streamlined cross-border customs clearance, AI can cut delivery lead times, eliminate major pain points and bottlenecks in cross-border logistics, and accelerate the intelligent, efficient, and collaborative transformation of CBEC supply chains.

In terms of the second core channel, which relates to consumer demand and behavior, it has been argued that artificial intelligence lowers consumers' information search costs, eases the cognitive load caused by processing abundant product data, raises purchase willingness, and optimizes matching efficiency between buyers and commodities, as well as the quality of consumer decisions [33,34]. It is indicated that intelligent data analytics allow enterprises to deliver customized communications and refine decision-making by mining consumer information [35,36]. In some cases, firms can even predict latent user demands ahead of consumers themselves and thus cultivate new consumption trends through innovative business practices.

Artificial intelligence can also leverage machine learning to replicate human perception, reasoning, and interactive functions, delivering tailored product recommendations to individual users, while customized suggestion algorithms can improve consumer satisfaction, stimulate purchasing intentions, and boost conversion and repurchase rates simultaneously [37]. For example, mainstream shopping applications recommend matching goods and promotional activities based on users' search keywords and browsing trajectories.

Drawing on the above analysis of AI's two core channels, this study puts forward the following research hypothesis:

Hypothesis 2. *Artificial intelligence promotes the high-quality development of CBEC by enhancing logistics capabilities and stimulating consumption.*

2.3. The Threshold Characteristics of Artificial Intelligence, High-Quality Development of CBEC, and Human Capital

Artificial intelligence (AI) has become one of the most influential digital technologies in recent decades. However, as a knowledge-intensive technology, it inherently requires a highly skilled workforce and thus represents a skills-biased technological advance [38,39]; therefore, human capital is needed to facilitate its integration into the cross-border e-commerce industry [40]. Indeed, the application of complex equipment and the intensification of research and development activities will significantly increase enterprises' demand for highly skilled labor and further reduce the employment of low-skilled workers [41,42]. Furthermore, after CBEC enterprises have introduced AI product selection models, intelligent marketing systems, and automated customer service bots, the products cannot be put into use immediately; instead, they require multi-skilled personnel with a data-driven mindset to continuously fine-tune system parameters. This has driven demand

for technical and research and development personnel whilst simultaneously fostering human-machine interaction. Employees are encouraged to learn and use cutting-edge AI technologies, thereby deepening their understanding of AI and related technologies to better adapt to the changing nature of work in the AI era.

Moreover, even though AI systems can efficiently handle data processing, their ability to identify unstructured risks is limited, and they find it even more difficult to make judgements requiring ‘situational intelligence’, such as those involving institutional changes or cultural sensitivities. Thus, when human capital accumulation is insufficient, enterprises are constrained by a ‘skill gap’ and are unable to fully utilize the benefits brought by technology; the practical application of artificial intelligence enters a state of ‘having the equipment but lacking the talent’. Furthermore, it has been argued that integrating human capital into cross-border e-commerce operations can also stimulate innovation and accelerate the pace of innovation in new products and business models [43].

Ultimately, there is a trade-off in AI implementation: on the one hand, realizing the value of collaboration between humans and AI brings ‘invisible’ benefits to CBEC enterprises and their staff [44,45]; on the other hand, enterprises must recruit multi-skilled professionals who possess both data-driven thinking and international business capabilities. Such employees are tasked with operating AI tools, adjusting algorithmic outputs, and identifying risks present in CBEC transactions.

Thus, the following research hypothesis is posited:

Hypothesis 3. *The promotional effect of artificial intelligence on CBEC exhibits a threshold effect based on the level of human capital.*

3. Research Design

3.1. Model Construction

Following a Hausman test that yielded a p -value of less than 0.05, the following two-way fixed effects model is constructed to examine the impact of artificial intelligence on the high-quality development of CBEC:

$$Cbec_{pt} = \beta_0 + \beta_1 AI_{pt} + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (1)$$

where p denotes the province, t represents the year, AI represents the level of AI development, $Cbec$ denotes the high-quality development of CBEC in the province, $controls$ represents all control variables, $\gamma_p, \delta_t, \varepsilon_{pt}$ denote the firm-level fixed effect, the year-level fixed effect, and the random disturbance term, respectively, β_0 represents the constant term, and β_1, θ represent the variable coefficients.

To investigate the probable processes by which artificial intelligence facilitates the advancement of CBEC, a mediation model based on Equation (1) is constructed, where $log_{pt}, Consumption_{pt}$ represent the logistics capacity and consumption level, respectively.

$$log_{pt} = \alpha_0 + \alpha_1 AI_{pt} + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (2)$$

$$Cbec_{pt} = \beta_0 + \beta_1 AI_{pt} + \beta_2 log_{pt} + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (3)$$

$$Consumption_{pt} = \mu_0 + \mu_1 AI_{pt} + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (4)$$

$$Cbec_{pt} = \beta_0 + \beta_1 AI_{pt} + \beta_2 Consumption_{pt} + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (5)$$

To investigate the threshold effect, the following threshold effect model is constructed:

$$Cbec_{pt} = \beta_0 + \beta_1 AI_{pt} \cdot I(Hum_{pt} \leq \lambda) + \beta_2 AI_{pt} \cdot I(Hum_{pt} > \lambda) + \theta controls + \delta_t + \gamma_p + \varepsilon_{pt} \quad (6)$$

where Hum_{pt} denotes the extent of human capital; $I(\cdot)$ denotes the indicator function; and λ denotes the threshold value.

3.2. Selection of Variables

In this study, the level of cross-border e-commerce development (Cbec) is selected as the dependent variable. Based on a provincial-level analysis, It has been argued that factors including transportation infrastructure, foreign direct investment, and degree of openness are closely associated with the operational performance of cross-border e-commerce: circulation infrastructure, such as highways and railways, improves cross-border e-commerce operational performance by raising trade efficiency and reducing transaction costs, while foreign direct investment and openness also exert significant positive effects on cross-border e-commerce operational performance [46].

To reflect the long-term logistics carrying capacity and commodity circulation capacity in cross-border e-commerce development, this study uses railway mileage, highway mileage, and per capita express delivery volume, capturing both sustainable development capacity and efficiency performance. Foreign trade dependence, the number of foreign-invested enterprises, and outward foreign direct investment are selected to reflect regional openness, international market linkages, and the capacity for international resource allocation [47], so as to characterize the openness features and structural optimization of cross-border e-commerce development. The above indicators describe the foundational conditions for cross-border e-commerce development from the perspectives of logistics efficiency, openness, and resource allocation, consistent with the efficiency gains, sustainable development capacity, and structural optimization emphasized in high-quality development.

Next, an evaluation index system (Table 1) for the level of cross-border e-commerce development is constructed using core indicators such as foreign trade dependence [4]. First, the min–max normalization method is applied to standardize raw indicators and thus eliminate the impacts of dimensional differences and magnitude disparities across indicators. Then, objective weighting of each indicator is carried out based on the information entropy and coefficient of difference calculated for each indicator. Finally, the composite score is computed as the weighted sum of standardized indicator values multiplied by their respective weights.

Table 1. Indicator framework for Cbec development assessment.

Primary Indicator	Secondary Indicator	Tertiary Indicators	Weight
Level of Cbec	Logistics Infrastructure	Railway length (10,000 km), road length (10,000 km), per capita express delivery volume	0.1710
			0.1623
			0.1451
	Trade Infrastructure	Foreign trade dependence ratio,	0.1537
		number of foreign-invested enterprises,	0.1883
		value of outward direct investment	0.1796

The establishment of comprehensive pilot zones for cross-border e-commerce is a major initiative in China's efforts to build a new system for an open economy; the creation of these zones can significantly promote the development of cross-border e-commerce in cities [48]. As a form of digital infrastructure, broadband serves as a fundamental enabler for the development of cross-border e-commerce [49]. This paper selects the number of regional cross-border e-commerce comprehensive pilot zones and broadband penetration rate as indicators [50]. The validity of the indicator system is tested using the criterion correlation method, with broadband penetration rate measured as the number of households with broadband access per 100 households. As shown in Table 2, high-quality

development of cross-border e-commerce is significantly and positively correlated with both the number of comprehensive cross-border e-commerce pilot zones and broadband penetration at the 1% significance level, which is consistent with expectations and indicates that the constructed indicator system can effectively characterize the level of high-quality development in cross-border e-commerce.

Table 2. Test for the Correlation Between the Effect and the Criterion.

Variable	<i>Cbec</i>	<i>Cbec Pilot Zone</i>
<i>Cbec</i>	1	
<i>Cbec pilot zone</i>	0.65 ***	1
	<i>Cbec</i>	Broadband penetration
<i>Cbec</i>	1	
Broadband penetration	0.36 ***	1

Note: *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

Artificial intelligence (AI) is chosen as the core explanatory variable. Through precision marketing, improved production efficiency, efficient logistics, and business model innovation, artificial intelligence comprehensively drives the transformation of CBEC, from scale expansion to enhancements in quality and economy, serving as the core technological engine for achieving high-quality development; however, the existing literature has not yet established a unified measurement framework for measuring artificial intelligence. Scholars indirectly capture real-world AI adoption by measuring robot installation density [51]. Previous research use the number of AI patent applications as a proxy for artificial intelligence [10]. Some scholars develop an approach to identify AI firms using firm-level data extracted from the Tianyancha database [13]. These scholars [52] employ the natural logarithm of the number of regional AI enterprises to measure regional AI development for robustness checks. Thus, this study follows the approach adopted by previous scholars [13] and uses firm-level microdata from Tianyancha. Firms are identified as artificial intelligence enterprises if their business scopes contain AI-related keywords such as image recognition, computer vision, speech recognition, and sensors. The natural logarithm of the count of identified AI firms is then constructed to proxy the level of regional artificial intelligence development.

Given that the development of CBEC may be influenced to varying degrees by other factors, the following indicators are designated control variables: ① employee count in the transportation, warehousing, and postal services industry, obtained via the logarithm of the employment figure in transportation, warehousing, and postal services; ② fiscal support level, measured by the ratio of local general public budget expenditure to regional gross domestic product; and ③ government policy support intensity, with a government document being regarded as a policy document supporting cross-border e-commerce development if it is found via web crawling and text mining techniques to contain keywords such as encourage and promote in relation to cross-border e-commerce. The total number of such documents is used to quantify government policy support intensity.

Logistics capacity and consumer expenditure are chosen as mediating variables. It is known that AI promotes the high-quality development of CBEC by improving logistics networks, enhancing logistics capacity, and stimulating consumer expenditure; thus, based on existing research, in this study, freight turnover (W_1) and passenger turnover (W_2) are combined into a single indicator, which is then logarithmized to measure logistics capacity

(Logistics), as specified in Equations (7) and (8). Per capita consumption expenditure is adopted to measure consumption level (Consumption) [53,54].

$$w_1 = -0.0009W_2^2 + 2.6581W_2 - 22.116 \quad (7)$$

$$Logistics = l_n(W_1 + w_1) \quad (8)$$

Human capital level (Hum) is chosen as the threshold variable. In the digital economy era, human capital is not only a source of technological progress, but also a key ‘adapter’ facilitating the deep integration of general-purpose technologies with the real economy. The relative size of the high-skilled workforce directly reflects the regional level of human capital. Following the existing approach [55], this study measures the human capital in each province by comparing the percentage of students enrolled in higher education institutions to the overall population.

3.3. Sources of Data and Descriptive Statistics

This research employs a sample comprising data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) obtained from 2013 to 2023 as the research subject and constructs a panel data model. The CNRDS database and the *China National Statistical Yearbook*, among others, are the sources of the information. Table 3 displays the descriptive statistics for every variable.

Table 3. Descriptive statistics.

Variable	Observations	Mean	Standard Deviation	Min.	Max.
<i>AI</i>	330	8.645	1.481	5.081	12.467
<i>Cbec</i>	330	0.182	0.083	0.029	0.555
<i>lnEmployment</i>	330	10.078	0.778	7.96	12.026
<i>Fin</i>	330	0.253	0.106	0.105	0.738
<i>Policy</i>	330	15.918	22.180	0	144
<i>Logistics</i>	330	8.562	0.879	6.432	10.446
<i>Consumption</i>	330	9.832	0.359	9.023	10.869

4. Empirical Analysis

4.1. Results of the Baseline Regression

This study includes three rounds of regression, and the results of the baseline regression are shown in Table 4, with columns (1), (2), and (3) representing the cases without two-way fixed effects and control variables, with two-way fixed effects, and with both control variables and two-way fixed effects, respectively. The coefficients of the core explanatory variables in all three regressions are significantly positive, at 0.023, 0.052, and 0.058, respectively. In this way, Hypothesis 1 is validated; specifically, it is found that AI can steadily and significantly promote the high-quality development of CBEC.

Table 4. Initial regression outcomes.

	(1)	(2)	(3)
<i>AI</i>	0.023 *** (0.003)	0.045 *** (0.009)	0.053 *** (0.010)
<i>lnEmployment</i>			−0.017 (0.012)
<i>Fin</i>			0.206 * (0.102)
<i>Policy</i>			0.0004 (0.000)
Individual fixed effects	No	Yes	Yes
Time fixed effects	No	Yes	Yes

Table 4. *Cont.*

	(1)	(2)	(3)
<i>N</i>	330	330	330
<i>R</i> ²	0.615	0.632	0.696

Note: * $p < 0.1$, *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

4.2. Robustness Tests

To ensure the robustness of our analysis, we control for the impact of the COVID-19 pandemic, the outbreak of which represented a major external shock to both trade globalization and the development of the cross-border e-commerce (CBEC) industry. This unprecedented health crisis disrupted global supply chains, imposed restrictions on cross-border logistics, and altered consumer behavior dramatically. Consequently, failing to account for the pandemic's influence could bias the estimated coefficients of other explanatory variables.

Robustness testing is performed by excluding observations from 2020 to 2022. Column (1) of Table 5 indicates that, after accounting for the pandemic's influence, the orientation and importance of the projected coefficient of the influence of artificial intelligence on the high-quality advancement of CBEC are largely unchanged, thereby reinforcing the validity of the previously presented baseline regression results.

Table 5. Results of the robustness test.

	(1)	(2)	(3)	(4)
	Excluding Pandemic Disturbances	Replacing Core Explanatory Variable	Lagging the Variable by One Period	Replacing the Interpreted Variable
<i>AI</i>	0.074 *** (0.011)	0.018 * (0.009)	0.059 *** (0.013)	0.057 *** (0.011)
Constant term	−0.267 * (0.151)	0.046 (0.145)	−0.187 (0.135)	−0.136 (0.121)
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
<i>N</i>	240	330	300	330
<i>R</i> ²	0.685	0.645	0.697	0.710

Note: * $p < 0.1$, *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

To further evaluate the resilience of the baseline regression findings, this study adheres to the methodology established by replacing the core explanatory variable with the number of AI patent applications and conducting the regression again [10]. Column (2) of Table 5 shows the regression results following this replacement, revealing that the core estimate continues to meet the significance criterion at the 10% level and thereby indicating that the outcomes are relatively reliable.

Next, a regression using the core explanatory variable lagged by one period is conducted to address potential endogeneity issues. Column (3) of Table 5 presents the regression results using a one-period lag. Owing to missing values for a subset of observations in 2012, the lagged regression employs data spanning 2014 to 2023. The coefficient on the lagged variable remains statistically significant at the 1% level and consistent with our earlier findings, implying a significant positive association between artificial intelligence and cross-border e-commerce.

Replacing the interpreted variable: Following the existing approach, this paper employs the equal-weight method—a subjective weighting technique—to reconstruct the dependent variable and conduct a regression analysis [56]. The results in Table 5 show that,

although there are some differences in the regression coefficients, their signs and levels of significance are generally consistent with those of the baseline model. This indicates that changes in the weights have a minimal impact on the regression results, suggesting that the findings are robust.

4.3. Testing of the Mediating Mechanism

Building on the above findings, the potential mechanisms underlying the relationship between the two variables are explored via mediation analysis conducted in accordance with the three-step mediation test [57]. Columns (1) and (3) of the regression results indicate that artificial intelligence exerts a considerable, favorable influence on both logistical capacity and consumption growth. The results in columns (2) and (4) indicate that the positive impact of artificial intelligence on the high-quality development of CBEC is realized through the enhancement of logistics capacity and the release of consumption potential. In this way, Hypothesis 2 is validated.

Table 6 reports the results of the Sobel test, with all estimates in the table exported from Stata15.0 and some values rounded to four decimal places. The Sobel Z statistic verifies the existence of partial mediation, and the mediation proportions of logistics capacity and consumption expenditure are 40.27% and 17.02%, respectively.

Table 6. Results of the Sobel mediation test.

	(1)	(2)	(3)	(4)
	<i>Logistics</i>	<i>Cbec</i>	<i>Consumption</i>	<i>Cbec</i>
<i>AI</i>				
<i>Logistics</i>	0.7544 *** (0.069)	0.0319 *** (0.008)	0.0808 *** (0.016)	0.0442 *** (0.007)
<i>Consumption</i>		0.0285 *** (0.006)		0.1122 *** (0.025)
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	330	330	330	330
Direct effect		0.0319 *** (0.009)		0.0442 *** (0.007)
Indirect effect		0.0215 *** (0.005)		0.0091 *** (0.003)
Total effect		0.0533 *** (0.010)		0.0533 *** (0.010)
Sobel Z		4.555 ***		3.376 ***
Adj-R ²		0.9498		0.9491
Proportion of mediating effect		0.4027		0.1702

Note: *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

4.4. Threshold Effect Test

The impact of artificial intelligence on the high-quality development of CBEC may show non-linear patterns due to differences in human capital levels. Thus, the panel threshold regression model introduced by Hansen is employed, with human capital (*Hum*) as the threshold variable, to examine the threshold effect of artificial intelligence on the high-quality development of CBEC. We conduct 300 bootstrap resampling replications, set the number of grid points to 100, and apply 1% trimming at both tails of the threshold variable. The appropriate test results are provided in Table 7. The positive effect of artificial intelligence on the high-quality development of CBEC has a significant single threshold at a human capital level of 0.0167; the 95% confidence interval is [0.0166, 0.0168], revealing the role of human capital in this context. Consequently, it is determined that, in its endeavors to further the high-quality growth of CBEC, artificial intelligence has a non-linear relationship with human capital levels acting as a threshold.

Table 7. Outcomes of the threshold effect assessment.

Threshold Variable	Threshold Test	Threshold Value	F-Value	<i>p</i> -Value	Critical Value		
					1%	5%	10%
<i>Hum</i>	Single threshold	0.0167	53.08	0.007 ***	50.083	28.123	25.425
	Double threshold	0.0167	13.30	0.378	57.908	31.765	23.973
	Triple threshold	0.0185	8.98	0.560	39.629	24.836	22.306

Note: *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

The results in Table 8 show that artificial intelligence drives the high-quality development of CBEC, with positive coefficients on both sides of the human capital threshold. There is, however, a slight difference in the coefficient values: when the degree of human capital is below the limit ($Hum \leq 0.0167$), the coefficient for the impact of AI is 0.050; when the degree of human capital exceeds the limit ($Hum > 0.0167$), the coefficient rises to 0.054.

Table 8. Regression results for the threshold effect.

	($Hum \leq 0.0167$)	($Hum > 0.0167$)
$AI \cdot I$	0.050 *** (0.009)	0.054 *** (0.009)
Control variables	Yes	Yes
Individual fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
<i>N</i>	57	273
R^2	0.727	0.727

Note: *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

These results suggest that elevated amounts of human capital can enhance the function of AI in driving the high-quality development of CBEC; however, the difference in coefficients on either side of the threshold is small, amounting to an increase of only 0.004.

Although the positive effect of AI on the high-quality development of CBEC rises once human capital crosses the threshold, the magnitude of this increase is modest. One possible reason for this is that artificial intelligence technology has a certain degree of universality; in regions where human capital levels are relatively low, cross-border e-commerce enterprises can still rely on basic AI applications—such as machine translation and intelligent customer service—to improve service efficiency and increase corporate profits. Alternatively, artificial intelligence relies on human capital to perform key operations such as information processing and content creation [21]; thus, lags in AI education may be behind this finding.

4.5. Heterogeneity Test

The heterogeneity analysis in this paper covers two aspects: regional heterogeneity and heterogeneity in e-commerce procurement activity. Following the existing approach [58], this paper employs the Fisher combined test to further examine differences in coefficients between groups. Based on the Bootstrap method with 1000 samples, the p -values from the test of differences in coefficients between groups in Table 9 indicate that the impact of artificial intelligence on cross-border e-commerce differs significantly between the eastern and central–western regions, as well as between regions with high and low levels of e-commerce activity.

There are certain disparities among different regions in China in terms of economic development levels, the foundation of the artificial intelligence industry, digital infrastructure development, and the degree of openness to the outside world. The central and western regions face issues such as inadequate infrastructure, limited service capacity, and lower economic levels [59]. Following the existing approach [60], this paper divides the sample

into the eastern region (with the Northeast region included in the eastern region) and the central and western regions. The results in Table 9 show that in the eastern region, artificial intelligence exhibits the most significant positive correlation with the high-quality development of cross-border e-commerce; however, the impact on the central and western regions is relatively minor. One possible explanation for this is that the eastern area has a stronger ability to use artificial intelligence to empower CBEC as it predominantly comprises coastal cities, has several national-level foreign trade ports, has convenient external transportation, has well-developed supporting infrastructure, engages in a high volume of cross-border trade, and has relatively complete digital infrastructure. The central and western regions may be limited by factors such as less convenient external connections and less developed digital infrastructure, which result in low levels of cross-border trade and difficulties in implementing artificial intelligence technologies across relevant industries.

Table 9. Outcomes of the heterogeneity assessment.

	(1)	(2)	(3)	(4)
	East	Central and Western	High e-Commerce Activity	Low e-Commerce Activity
<i>AI</i>	0.076 *** (0.014)	0.019 * (0.010)	0.068 *** (0.021)	0.019 (0.014)
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
<i>N</i>	143	187	165	165
<i>R</i> ²	0.687	0.852	0.668	0.813
<i>p</i> -value for differences in coefficients between groups		0.036 **		0.063 *

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, heteroscedastic-robust standard errors in brackets.

To examine heterogeneity in e-commerce purchasing activity, the per capita e-commerce spending in 30 provinces is used as a measure of heterogeneity in e-commerce activity. The per capita e-commerce spending data for all 330 province-year combinations were sorted in ascending order, and the 50th percentile was selected as the grouping threshold. Specifically, observations with per capita e-commerce spending greater than or equal to this median were classified as the “high activity” group, while those below the median were classified as the “low activity” group. Finally, a grouped regression analysis was conducted. Table 9 shows that in high-interest regions, there is a significant positive correlation between artificial intelligence and the high-quality development of cross-border e-commerce, whereas the impact on low-interest regions is not significant. Possible reasons for this include the fact that high-activity regions typically have more mature digital infrastructure and a wider range of e-commerce applications. Therefore, companies in these regions are able to more effectively turn AI technologies—such as intelligent product selection, precision marketing, multilingual customer service, and cross-border logistics optimization—into real improvements in cross-border transaction efficiency and thereby gain greater benefits from the technology. In contrast, low-activity regions may be limited by weaker digital foundations, less complete industry chains, or a more limited ability to use new technologies, so the benefits of AI have not yet been fully realized.

5. Conclusions and Discussion

5.1. Theoretical Contribution

In this study, the effects, causes, and variability of artificial intelligence in relation to the high-quality advancement of CBEC are rigorously analyzed utilizing panel data from 30 Chinese provinces for the period 2013 to 2023. The conclusion is that there is a significant positive correlation between artificial intelligence and the high-quality development of cross-border e-commerce, and this finding remains valid even after a series of robustness tests (including controlling for the impact of the pandemic, substituting key explanatory variables, applying a one-period lag to the variables and replacing the dependent variable). Thus, this research verifies the facilitating effect of artificial intelligence on the high-quality development of cross-border e-commerce, consistent with the previous findings [21], who argued that artificial intelligence enables better integration and effective global operations and facilitates centralized corporate control. The results also support the view that AI helps international firms such as cross-border e-commerce enterprises acquire customer and market information and conduct in-depth competitor analysis. The conclusion that artificial intelligence promotes the high-quality development of cross-border e-commerce aligns with the existing findings [61], who stated that artificial intelligence can deliver high-value digital services.

Regarding human capital, it has been argued that cross-border e-commerce exports impose higher requirements on talent and greater demand for highly educated workers [62], while previous research shows that artificial intelligence relies on human capital to perform key operations such as information processing and content creation [21]. This resonates with this study's finding that the high-quality development of cross-border e-commerce features a human capital threshold effect. That is, through the development of a threshold model, this study found that the positive correlation between artificial intelligence and CBEC exhibits a single-threshold effect determined by the level of human capital: when human capital is below 0.0167, the coefficient of AI is 0.054; once human capital exceeds this value, the coefficient rises to 0.057. Although the difference in coefficients before and after the threshold is small, it still demonstrates that the accumulation of human capital can reinforce the technological spillover effects of AI, consistent with the logic of complementarity between technology and skills.

An analysis of the mechanisms involved further revealed that the positive impact of artificial intelligence on the high-quality development of cross-border e-commerce can be achieved through improvements in logistics capabilities and the unlocking of consumer potential. The results of the mediation analysis indicate that logistics capacity accounts for 40.27% of the mediation effect, whilst consumer expenditure accounts for 17.02%; both indicators were found to be significant in the Sobel test.

Consideration of the heterogeneity revealed that the influence of AI on CBEC exhibits significant regional and application-scenario difference: at the regional level, the impact of AI is most pronounced in the eastern regions; however, the correlation is weaker in the Mid-West, reflecting regional disparities in the development of new digital infrastructure and the level of openness to the outside world. In terms of e-commerce procurement activity, there is a significant positive correlation between artificial intelligence and the high-quality development of cross-border e-commerce in high-interest regions, whereas the impact on low-interest regions is not significant. This demonstrates that a mature e-commerce ecosystem is better positioned to harness the benefits of artificial intelligence.

5.2. Practical and Policy Implications

This study has the following practical and policy implications: technology companies should be encouraged to forge close partnerships with CBEC enterprises, thereby promoting

the practical application of artificial intelligence within the sector; the advancement of transnational logistics networks should be accelerated by applying artificial intelligence to key processes such as warehouse scheduling, route planning, and customs clearance coordination; and generative artificial intelligence should be utilized to create immersive shopping experiences, effectively stimulating consumer purchasing intent and fostering an industry development model driven by the dual engines of logistics and consumption.

Furthermore, differentiated policies should be formulated based on regional characteristics. The eastern regions should continue to play a leading role in promoting cutting-edge applications of AI technology, while the central and western areas must accelerate the development of digital infrastructure, strengthen talent cultivation and recruitment, increase the degree of receptiveness to external influences, and narrow the digital gap with the eastern regions. For regions with relatively low e-commerce activity, policy support should be increased, prioritizing the construction of e-commerce ecosystems suitable for local development and enhancing enterprises' ability to absorb and apply new technologies.

5.3. Constraints and Avenues for Future Research

This study possesses certain constraints regarding its measuring markers. Whilst the quantity of artificial intelligence firms indicates the extent of AI progress and is to some extent representative, it fails to fully reflect the multidimensional characteristics of the current state of AI across different regions. Furthermore, this study was able to reveal regional differences and variations in application scenarios through heterogeneity analysis; however, due to the limitations of the sample scope, it was not possible to further examine heterogeneous characteristics in contexts involving different CBEC models, enterprise sizes, or product categories. The empirical regressions employ heteroskedasticity-robust standard errors but do not cluster standard errors at the provincial level, so residual correlation within provinces remains unaddressed.

Future research should further explore the following domains: Firstly, a more comprehensive evaluation framework for the development of artificial intelligence should be established, taking into account multidimensional indicators such as patents, investment scale, and technological application scenarios, to more precisely characterize the degree of development and impact of artificial intelligence. Secondly, by integrating micro-level data from enterprises, research should adopt a more granular perspective to explore in depth the differentiated impacts of artificial intelligence across various contexts whilst focusing on its long-term dynamic effects on and potential non-linear characteristics in the high-quality development of CBEC.

Author Contributions: M.Z.: Conceptualization, Data curation, Writing—review and editing, Supervision, Visualization. L.Z.: Methodology, Formal analysis, Writing—original draft. All authors have read and agreed to the published version of the manuscript.

Funding: The work reported in this paper was supported by National Natural Science Foundation of China (72101084).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wu, B.; Chang, X.; Zhou, J.; Gu, C.; Zhan, X. The Mechanism and Empirical Study of the Impact of Cross-Border E-Commerce Development Level on Export Trade under the RCEP Framework. *Innov. Entrep. Manag.* **2025**, 82–98.
2. Meng, T.; Wang, C.J.; Fan, P.H. Research on Strategies for the High-Quality Development of Cross-Border E-Commerce from the Perspective of Digital Economy. *Int. Trade* **2022**, 60–67.
3. Song, Q. Causes of Risks Faced by Chinese Cross-Border E-Commerce Enterprises in the Development of ‘Overseas Warehouses’ and Preventive Measures. *Foreign Trade Econ. Pract.* **2017**, 84–87.
4. Guo, Y. Research on the Development Level and Influencing Factors of Cross-Border E-Commerce in China. *Reg. Res. Dev.* **2024**, 43, 16–21.
5. Huang, Q.H.; He, J. The “third industrial revolution” and China’s economic development: From the perspective of techno-economic paradigm shift. *China Ind. Econ.* **2013**, 5–18.
6. Xu, H.; Zhang, Y.L.; Cao, Y.J. Technology spillovers of digital economy and dynamic co-opetition policies. *Manag. World* **2020**, 36, 63–84.
7. Shen, K.R.; Lin, J.W. The Mechanism and Promotion Path of Artificial Intelligence Empowering Industrial Transformation. *Econ. Rev.* **2025**, 55–65+136.
8. Xu, P.; Xu, X.Y. The Logic and Analytical Framework of Enterprise Management Transformation in the Age of Artificial Intelligence. *Manag. World* **2020**, 36, 122–129+238.
9. Wang, J.; Chang, H. Research Progress on the Impact of Artificial Intelligence on the Labor Market. *Econ. Dyn.* **2021**, 146–160.
10. Yao, J.; Zhang, K.; Guo, L.; Feng, X. How Does Artificial Intelligence Improve Enterprise Productivity? A Perspective Based on the Adjustment of Labor Skill Structure. *Manag. World* **2024**, 40, 101–116+133+117–122.
11. Liu, J.; Chang, H.; Forrest, Y.J.; Yang, B. Influence of Artificial Intelligence on Technological Innovation: Evidence from the Panel Data of China’s Manufacturing Sectors. *Technol. Forecast. Soc. Change* **2020**, 158, 120142. [[CrossRef](#)]
12. Kromann, L.; Malchow-Møller, N.; Skaksen, J.R.; Sørensen, A. Automation and Productivity: A Cross-Country, Cross-Industry Comparison. *Ind. Corp. Change* **2020**, 29, 265–287. [[CrossRef](#)]
13. Wang, L.H.; Jiang, H.; Dong, Z.Q. Will Industrial Intelligence Reshape the Geographical Pattern of Enterprises? *China Ind. Econ.* **2022**, 137–155.
14. Acemoglu, D.; Autor, D. What Does Human Capital Do? A Review of Goldin and Katz’s “The Race between Education and Technology”. *J. Econ. Lit.* **2012**, 50, 426–463. [[CrossRef](#)]
15. Zhao, S.F. Strategies for Artificial Intelligence Empowering the Development of Cross-Border E-Commerce. *Entrepreneur Daily*, 18 October 2025, 003.
16. He, J.Y. Artificial Intelligence Empowers the Development of Cross-Border E-Commerce for Paper-Based Cultural and Creative Products. *China Pulp Pap.* **2025**, 44, 220–221.
17. Song, H. Digital Transformation Path of Cross-Border E-Commerce Logistics Enterprises. *Management* **2026**, 9, 51–60. [[CrossRef](#)]
18. Li, S.W.; Luo, J.L.; Zhang, Z.F. How Does AI Capability Promote Value Co-Creation in Enterprises? An Exploratory Case Study Based on Enterprise-Customer Interaction. *China Ind. Econ.* **2023**, 174–192.
19. Agrawal, A.; Gans, J.; Goldfarb, A. *The Economics of Artificial Intelligence*; University of Chicago Press: Chicago, IL, USA, 2019.
20. Fügener, A.; Grahl, J.; Gupta, A.; Ketter, W. Will humans-in-the-loop become Borgs? Merits and pitfalls of working with AI. *MIS Q.* **2021**, 45, 1527–1556. [[CrossRef](#)]
21. Buckley, P.J.; Elia, S.; Gaur, A.; Krakowski, S.; Kuivalainen, O.; Pedota, M. Artificial intelligence and international business: Theoretical challenges, strategic implications, and research agenda. *J. World Bus.* **2026**, 61, 101710. [[CrossRef](#)]
22. Garaus, M.; Treiblmaier, H.; Wagner, U.; Garaus, C. Innovating the experience economy: How novel technologies transform customer experiences. *Digit. Bus.* **2025**, 5, 100134. [[CrossRef](#)]
23. Brynjolfsson, E.; Rock, D.; Syverson, C. *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics*; NBER Working Paper, No.w24001; National Bureau of Economic Research (NBER): Cambridge, MA, USA, 2017.
24. Goldfarb, A.; Taska, B.; Teodoridis, F. Could Machine Learning Be a General Purpose Technology? A Comparison of Emerging Technologies Using Data from Online Job Postings. *Res. Policy* **2023**, 52, 104653. [[CrossRef](#)]
25. Du, C.Z.; Li, Y.W. Research on the mechanism and path of empowering the development of new quality productive forces with “artificial intelligence +”. *Soc. Sci. Dig.* **2026**, 4, 120–131.
26. Zhai, L. Optimization of Logistics Systems Based on Artificial Intelligence. *J. Shanxi Univ. Financ. Econ.* **2024**, 46, 77–79.
27. Liu, C.; Huo, B.; Liu, S.; Zhao, X. Effect of information sharing and process coordination on logistics outsourcing. *Ind. Manag. Data Syst.* **2015**, 115, 41–63. [[CrossRef](#)]
28. Cheng, L. “Artificial intelligence + logistics”: Technological tension and structural optimization. *People’s Trib.* **2025**, 2, 35–40.
29. Liu, W.H.; Wang, S.Y.; Zhou, Z.C. Research on the influence path of Industry 4.0 technology on the integration of logistics and manufacturing industries—A study based on typical case collections collected by the National Development and Reform Commission. *Syst. Eng. Pract.* **2025**, 45, 2245–2263.

30. Li, X.; Cai, L.; Yuen, K.F. Enhancing consumer engagement in virtual shopping: The role of social presence in shaping switching intentions. *Electron. Commer. Res. Appl.* **2026**, *76*, 101580. [[CrossRef](#)]
31. Song, H.; Han, M.W.; Shen, L.Y. The Role of Artificial Intelligence in Shaping Supply Chain Resilience: A Case Study Based on Meichuang's Global After-Sales Supply Chain Management Practices. *China Ind. Econ.* **2024**, 174–192.
32. Daios, A.; Kostavelis, I. Artificial intelligence and sustainable supply chain performance: A trade-off-aware evaluation framework. *Sustainability* **2026**, *18*, 5907. [[CrossRef](#)]
33. Tan, C.H.; Teo, H.H.; Benbasat, I. Assessing screening and evaluation decision support systems: A resource-matching approach. *Inf. Syst. Res.* **2010**, *21*, 305–326. [[CrossRef](#)]
34. Pereira, R.E. Influence of query-based decision aids on consumer decision making in electronic commerce. *Inf. Resour. Manag. J.* **2001**, *14*, 31–48. [[CrossRef](#)]
35. Yang, Z.; Wang, W.N.; Chen, J. R&D Cooperation, Digital Empowerment and Corporate Innovation Performance: Micro-Evidence from Chinese Manufacturing Enterprises. *Comp. Econ. Soc. Syst.* **2023**, 137–150.
36. Redda, E.H. AI-Driven Digital Marketing and Responsible Consumption: The Mediating Role of Marketing Intelligence in Advancing SDG 12. *Sustainability* **2026**, *18*, 3912. [[CrossRef](#)]
37. Jiao, L. The Impact of Artificial Intelligence Development on the New Consumer Market: An Analysis from the Perspective of Distribution Efficiency. *Bus. Econ. Res.* **2025**, 63–66.
38. Liu, S.H.; Leng, H.T. How do artificial intelligence applications affect urban financial resilience? *Econ. Probl.* **2026**, 41–50.
39. Yan, S.; Jin, S.; Wang, J.; Yuan, L. How Does Artificial Intelligence Capability Foster Sustainable Green Innovation? Evidence from Chinese Listed Firms. *Sustainability* **2026**, *18*, 6803. [[CrossRef](#)]
40. Guo, Y.B.; Hu, L.J. Research on the Impact of Artificial Intelligence and Human Capital on Industrial Structure Upgrading: Empirical Evidence from 30 Provinces in China. *Soft Sci.* **2022**, *36*, 15–20.
41. Koch, M.; Manuylov, I.; Smolka, M. Robots and firms. *Econ. J.* **2021**, *131*, 2553–2584. [[CrossRef](#)]
42. He, X.G.; Liu, K.M. Robots, work tasks and employment polarization effect: Evidence from Chinese industrial firms. *J. Quant. Tech. Econ.* **2023**, *40*, 52–71.
43. Tian, T.; Jiang, W.; Tong, D.; Wang, G.; Zheng, H. Artificial intelligence technology adoption and green innovation of manufacturing enterprises—From the perspective of heterogeneous corporate human capital endowments. *Xinjiang Soc. Sci.* **2026**, 34–47, 190–191.
44. Seeber, I.; Bittner, E.; Briggs, R.O.; de Vreede, T.; De Vreede, G.J.; Elkins, A.; Schwabe, G. Machines as teammates: A research agenda on AI in team collaboration. *Inf. Manag.* **2020**, *57*, 103–174. [[CrossRef](#)]
45. Wu, X.L.; Xiao, J.H.; Wu, J. New Forms of Organizational Learning in Human-AI Collaboration: A Multi-Case Study Based on Scenario Perspective. *China Ind. Econ.* **2022**, 175–192.
46. Yuan, K. The Impact of Trade Facilitation on Cross-border E-commerce Operational Performance under the Dual Circulation Background: Empirical Evidence Based on Provincial Panel Data. *J. Commer. Econ.* **2021**, 89–92.
47. Zhang, X.W.; Wang, S.J. Evolutionary Characteristics and Influencing Factors of High-level Opening-up in China's Land Border Areas. *World Reg. Stud.* **2026**, *35*, 154–167.
48. Ma, S.; Guo, J. How institutional innovation affects China's cross-border e-commerce exports: Empirical evidence from the establishment of comprehensive pilot zones. *Manag. World* **2022**, *38*, 83–102.
49. Zhao, T.; Zhang, Z.; Liang, S.K. Digital economy, entrepreneurial activity and high-quality development: Empirical evidence from Chinese cities. *Manag. World* **2020**, *36*, 65–76.
50. Li, H.; Zhang, M.; Qu, X.; Liu, Q.; Zheng, H.; Mei, M. Construction and application of an indicator system for high-quality enterprise development. *J. Beijing Inst. Technol. (Soc. Sci. Ed.)* **2026**, *28*, 129–143.
51. Liu, Y.; Wang, Z.; Li, M. Heterogeneous impact of artificial intelligence on carbon emission intensity: Empirical test based on provincial panel data in China. *Front. Ecol. Evol.* **2024**, *11*, 1058505. [[CrossRef](#)]
52. Sun, X.; Song, Y.; Zhao, P.Y. How artificial intelligence affects labor income: Micro analysis and empirical test based on individual ability. *J. Shanxi Univ. Financ. Econ.* **2022**, *44*, 17–29.
53. Fan, F.Z.; Peng, T.T. Research on the Impact of Digital Inclusive Finance on Rural Residents' Consumption in China. *Soc. Sci. Front.* **2023**, 82–91.
54. Tan, Q.M.; Feng, L.Y.; Ge, Y. Research on the Contribution of Logistics Capacity to Regional Economy. *Mod. Econ. Explor.* **2003**, 22–24.
55. Chen, Y.W.; Guo, C.B. Industrial Diversification Agglomeration, Human Capital and Urban Economic Resilience. *Stat. Decis.* **2024**, *40*, 93–97.
56. Liu, Y.B.; Chen, L.P.; Cheng, S.X. The common prosperity effect of major national strategic regional construction. *J. Financ. Econ.* **2026**, *52*, 19–35.
57. Wen, Z.; Zhang, L.; Hou, J.; Liu, H. Testing Procedure for Mediating Effects and Its Application. *Acta Psychol. Sin.* **2004**, *36*, 614–620.

58. Li, C. Structural Monetary Policy, Digital Economy and High-quality Economic Development: From the Perspective of Economic Growth Momentum. *Inq. Into Econ. Issues* **2024**, *12*, 50–67.
59. Su, W.H.; Wang, Y.Y. Statistical measurement of the development level of China's cross-border e-commerce comprehensive pilot zones. *J. Bus. Econ. Manag.* **2017**, 13–22.
60. Shen, J.; Chang, Z.Z.; Mao, P. National unified large market construction and the development of new-quality productive forces: Empirical analysis based on China's provincial panel data. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2024**, *30*, 56–71.
61. Queiroz, M.M.; Beatriz, A.; Bagherzadeh, M. Crowdsourcing-enabled AI: Unlocking value in digital services. *Int. J. Prod. Econ.* **2025**, *283*, 109586. [[CrossRef](#)]
62. Ma, S.; Lin, Y.; Pan, G. Does cross-border e-commerce contribute to growth convergence? An analysis based on Chinese provincial panel data. *J. Glob. Inf. Manag.* **2021**, *29*, 86–111.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.