

FACTORS AFFECTING AI TECHNOLOGY ON EXPORT PERFORMANCE OF CHINESE CROSS-BORDER E-COMMERCE ENTERPRISES

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ABSTRACT

Drawing on the TOE framework, this study examined how AI technology affected the export performance of Chinese cross-border e-commerce (CBEC) enterprises through four factors including insufficient technological adaptability, insufficient AI integration in supply chain management (SCM), talent gap, and market competition pressure, with the first three identified as AI implementation barriers and the last as a positive competitive driver. Multiple linear regression and confirmatory factor analysis were performed on 469 valid survey responses, using SPSS 29.0 and AMOS 24.0. The results showed that insufficient technological adaptability ($\beta = -0.248$, $p < 0.001$), insufficient AI integration in SCM ($\beta = -0.239$, $p < 0.001$), and talent gap ($\beta = -0.333$, $p < 0.001$) negatively affected export performance, while market competition pressure had a positive effect ($\beta = 0.224$, $p < 0.001$). All four hypotheses were supported, with the talent gap showing the strongest negative coefficient. This study confirmed the TOE framework's applicability in CBEC, identifies the talent gap as a more critical bottleneck than technological infrastructure, and reveals that competitive pressure positively drives export performance in fragmented international markets, contrasting with domestic e-commerce findings. The results offer strategic guidance for CBEC enterprises to prioritize AI talent development, modular system integration, and leveraging competition for innovation.

Keywords: *AI Technology, Cross-border E-commerce, Export Performance, Influencing Factors, TOE Theory*

1. INTRODUCTION

Chinese cross-border e-commerce (CBEC) enterprises have moved quickly to adopt AI, yet adoption alone does not guarantee improved export performance, as technological, organizational, and competitive conditions shape the outcome, and this study examines these conditions. Over the past five years, AI technology has penetrated into major industries such as healthcare, finance, manufacturing, and retail. AI technology can apply algorithms in CBEC to predict market trends and consumer behavior, thereby enabling enterprises to target markets and formulate marketing strategies, thus improving efficiency and competitive

advantage. Concurrently, Chinese CBEC enterprises have risen rapidly in the international trade field. Chinese enterprises use online platforms to sell products and services directly to overseas customers. In 2019, the scale of CBEC transactions in China reached CNY 10.8 trillion, a year-on-year increase of 16.6%. According to the China E-commerce Research Center, this figure will continue to grow. AI is primarily used for big data analysis, which can optimize product development and inventory management by understanding consumer demand and market trends. Secondly, intelligent customer service robots can provide 24/7 customer service, which enhances customer contentment and lowers

operational expenses. Finally, in terms of intelligent logistics and warehouse automation, it can enhance enterprises' operational efficiency, response speed **Error! Unknown switch argument..**

Advances in AI technology have brought potential for Chinese CBEC enterprises to optimize operations and expand international markets, but their actual application has not met expectations due to various restrictions. The unresolved question is why so many enterprises fail to translate AI adoption into export performance. Such a failure wastes resources, slows international response, and weakens competitiveness. It is a problem that concerns enterprise managers, policymakers, and AI service providers alike. Therefore, studying the barriers to AI application can significantly improve the export performance of CBEC enterprises. This study adopts the TOE framework, as AI adoption involves not only technical readiness, but also organizational resources and external competitive conditions. The four factors examined here correspond to the technology, organization, and environment dimensions, which allows the analysis to capture both internal barriers and external pressures. A survey-based quantitative design and a sample of Chinese CBEC enterprises are appropriate, because the study aims to estimate the relative influence of multiple factors on export performance in a leading cross-border e-commerce market.

Chinese CBEC enterprises face several challenges. Their existing technological infrastructure is not well adapted to AI and that there is a lack of AI professionals [3]. Moreover, international market competition is fierce. Supply chain management (SCM) has not fully integrated AI, resulting in low corporate efficiency [4].

The impact of AI implementation barriers on the export performance of Chinese CBEC enterprises deserves attention. From an internal perspective, insufficient technological adaptability, insufficient AI integration in SCM, and talent gap constitute three major bottlenecks. From an external environment perspective, market competition pressure can not be ignored either.

The core questions addressed in this study are as follows: (1) How does insufficient technological adaptability affect the export performance of Chinese CBEC enterprises? (2) How does insufficient AI integration in SCM affect the export performance of Chinese CBEC enterprises? (3) How does the talent gap affect the export performance of Chinese CBEC enterprises? (4) How does market competition pressure affect the export performance of Chinese CBEC enterprises?

The rest of this paper is organized as follows. The next Section reviews the relevant literature and develops the research hypotheses. Then the research methodology and data collection process are described. The subsequent section presents the empirical results and analysis. After that, it discusses the findings, their implications, limitations, and directions for future research. The last section concludes the study and provides a future outlook.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This section reviews the relevant literature and explores the impact of AI on the export performance of CBEC enterprises. It first provides an overview of AI technology and defines CBEC export performance in terms of sales, market share, and customer satisfaction. It then analyzes the application of AI in market forecasting, customer service, and SCM.

The influencing factors are explained from the aspects of insufficient technological adaptability, insufficient AI integration in SCM, talent gap, and market competition pressure. Based on the TOE theoretical framework, research gaps and the main contributions are identified, and four research hypotheses are proposed to support subsequent empirical research.

2.1 Overview of AI Technology

AI technology is used to build computer systems that can simulate human intelligence. Natural Language Processing (NLP) is a typical application scenario. With the help of machine learning, models can efficiently parse text data, extract semantic information, and complete corresponding tasks under certain instruction constraints. Furthermore, the role of artificial intelligence is not limited to data analysis. It can also introduce intelligent automation into business processes, allowing repetitive tasks to be handled more efficiently, thereby improving operational efficiency [5].

2.2 Definition of CBEC Enterprises' Export Performance

Export performance is a comprehensive indicator of how well a company translates its domestic competitive advantages into performance in overseas markets. It is typically used to assess the actual effectiveness of a company's overseas operations, rather than just focusing on investment or overseas processes. For CBEC companies,

export performance is often reflected in market sales results, such as sales revenue or exports, and is further examined through factors such as market share, customer demand, and brand influence. Ultimately, it is also reflected in profitability and overall connectivity [6].

2.3 Current Application Status of AI Technology in CBEC

AI is increasingly penetrating the CBEC sector. For example, Robotic Process Automation (RPA) can significantly improve processing efficiency while reducing human error [2]. Similarly, in the retail sector, AI can predict consumers' future purchasing behavior, assist in optimizing inventory, and analyze user browsing patterns. These capabilities are equally applicable to CBEC scenarios.

AI has boosted Chinese CBEC exports in many ways, such as market trend analysis, personalized recommendations, intelligent customer service, and supply chain optimization, all of which have already seen relatively clear applications. However, challenges such as data compliance and algorithmic bias still persist. This necessitates more profound cross-border ecological collaboration to address the evolving demands of the market.

2.4 Influence Factors of Chinese CBEC Enterprises' Export Performance

CBEC's rapid expansion has played a major role in China's economic growth. Yet, when it comes to penetrating international markets, the success of these enterprises depends on a wide range of complex factors.

2.4.1 Insufficient technical adaptability

For enterprises, addressing the difficulties of AI management adaptation often involves talent training, phased implementation, data governance optimization, along with multi-party collaboration.

In the actual application process, enterprises generally face the challenge of insufficient AI adaptability. Taking this as the starting point, the present article systematically explores the adaptability gap and its causes in the process of enterprise implementation of AI, and further proposes effective strategies to bridge the gap.

2.4.2 Insufficient AI integration in SCM

Insufficient AI integration in SCM restricts the export performance of CBEC enterprises. Although technologies such as predictive analysis can optimize inventory, shorten delivery, and improve demand forecasting, enterprises often find it difficult to integrate them due to lack of technical, financial, or organizational preparation, resulting in

low efficiency and weakening international market responsiveness and export competitiveness [2].

2.4.3 Talent gap

The talent gap in business management affects corporate competitiveness and development. A cross-country panel analysis of 15 countries from 2016 to 2022 found that AI skills have a significant short-term positive effect on firm productivity, emerging with a lag of a quarter and underscoring the necessity of continuously renewing investment in an AI-skilled labor force [7]. This finding suggests that a persistent shortage of AI talent makes it difficult for enterprises to utilize AI, leading to a decline in competitiveness and export performance.

2.4.4 Market competition pressure

At present, AI has become an important part of modern business. With the rapid development of technology, market competition has become increasingly fierce, and enterprises are under tremendous pressure. To ensure survival and long-term development, companies often invest resources in AI research and development, supplementing their technology and experience through collaborations with other companies. Simultaneously, companies need to gradually shift towards data-driven workflows, basing decisions more on data than experience. Furthermore, ethical compliance is also a crucial aspect. Overall, these practices help companies better leverage the competitive advantages of AI and drive sustainable growth on a more robust foundation [8].

2.5 Research Gaps

Although existing studies have examined AI applications in e-commerce, three gaps remain. First, firm-level evidence is still limited, as most studies focus on platform-level adoption or the potential benefits of AI rather than on how AI implementation barriers affect export performance in CBEC enterprises. Second, few studies have tested technological adaptability, SCM integration, talent gap, and competitive pressure within a single TOE-based model, which makes it difficult to compare their relative effects. Third, the mechanisms through which talent gap and competitive pressure shape export performance in fragmented cross-border markets remain underexplored, especially because competitive pressure may operate differently from domestic e-commerce. These gaps justify further investigation into how AI-related barriers and competitive drivers jointly influence CBEC export performance.

2.6 Research Contributions

This study makes several contributions. An analytical model was built in this study based on the TOE framework, incorporating four specific factors which are insufficient technological adaptability, insufficient AI integration in SCM, talent gap, and market competition pressure. This model provides a relatively complete analytical framework for understanding the impact mechanism of these factors on export performance. Methodologically, the empirical analysis collected 469 valid questionnaires and used multiple regression to examine the relationship between each factor and export performance. Practically, these findings offer actionable implications for CBEC enterprises, especially in terms of AI talent development, modular system integration, and competitive intelligence, which together provide a pathway for converting AI adoption into export performance.

2.7 TOE Theoretical Framework

The TOE framework is broken down into four key variables in Figure 1. The technology dimension involves the ability of an enterprise's existing infrastructure to support AI applications, while also focusing on the depth of AI embedding in SCM. The organizational dimension essentially reflects the issue of talent reserves, whether the enterprise has sufficient human resources to drive the implementation of AI. As for the environmental dimension, its core lies in the driving role of external competitive pressure on the enterprise's technology adoption decisions. Taken together, the framework suggests that the export performance of CBEC enterprises is shaped by the technological, organizational, and environmental dimensions together, and the four factors each exert their effects in distinct ways.

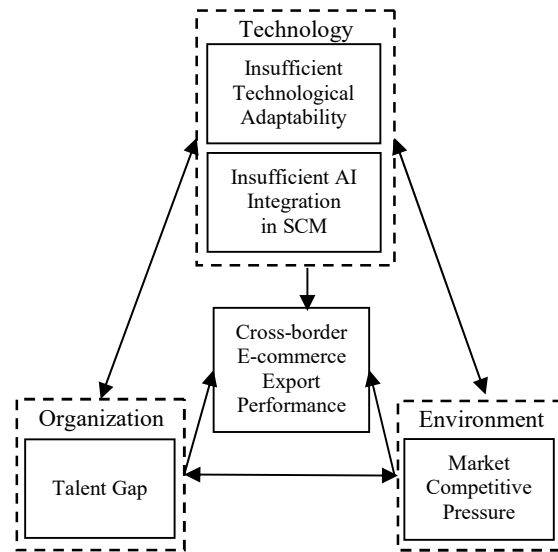


Figure 1: Technology-Organization-Environment (TOE) Framework

2.8 Research Hypotheses

Based on established theories, this study examines the influence mechanisms of the relevant variables. For the hypotheses, H1, H2, and H3 are set as negative effects, while H4 is set as a positive effect.

2.8.1 Insufficient technological adaptability has a negative influence on the export performance of CBEC enterprises

Technological readiness, IT resource availability, and organizational capabilities all significantly impact enterprise performance [9]. If CBEC enterprises lack the technological adaptability to keep pace, data integration is prone to problems, system compatibility is poor, and technical support is often inadequate. These issues slow down AI application efficiency and increase operating costs. Insufficient technological adaptability makes it difficult to improve business optimization and export performance. Based on this, this paper proposes the following hypotheses:

H1: Insufficient technological adaptability has a significant negative influence on the export performance of CBEC enterprises.

2.8.2 Insufficient AI integration in SCM has a negative influence on the export performance of CBEC enterprises

The effective AI integration in SCM can help improve operational efficiency, reduce costs, and enhance a company's ability to respond to market fluctuations. If not, it may cause logistics delays and inventory inefficiencies. Insufficient AI integration undermines delivery reliability as well as customer satisfaction, which in turn negatively

affects export performance [2]. For Chinese CBEC enterprises, a lack of AI integration could turn into a bottleneck when it comes to improving global competitiveness. Based on this, the following is formulated as an assumption.

H2: Insufficient AI integration in SCM has a significant negative influence on the export performance of CBEC enterprises.

2.8.3 Talent gap has a negative influence on the export performance of CBEC enterprises

Enterprises that employ AI-skilled workers achieve much higher total sales, and this effect is even stronger for those exporting [10]. This finding implies that a shortage of such professional talent directly limits an enterprise's capacity to compete in international markets. CBEC enterprises need such professional talents to maintain AI systems, and this in turn affects their market competitiveness as well as export performance. In addition, the combination of human and technological capital is necessary for achieving competitive advantage [11]. Given that a talent gap restricts AI implementation and also weakens market adaptability, it is likely to lead to diminished export rates. On these grounds, this study proposes the following hypothesis as H3.

H3: Talent gap has a significant negative influence on the export performance of CBEC enterprises.

2.8.4 Market competition pressure has a positive influence on the export performance of CBEC enterprises

It is widely recognized that competitive pressure drives corporate innovation and also encourages the adoption of AI technologies for the purpose of improving efficiency and competitiveness. Empirical research has demonstrated that competitive pressure has a positive and significant effect on technology adoption [12]. Market competition helps improve operational efficiency as well as customer experience, and in doing so promotes AI application and boosts export performance. On this basis, this study proposes the following hypothesis:

H4: Market competition pressure has a significant positive influence on the export performance of CBEC enterprises.

2.9 Conceptual Framework

Figure 2 shows the conceptual framework of this study. It was developed by drawing on a comprehensive review of the relevant literature together with the proposed hypotheses.

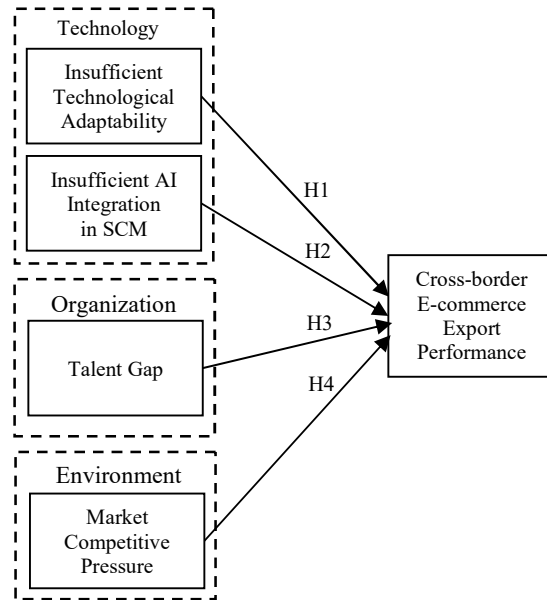


Figure 2: Conceptual Framework

3. RESEARCH METHODOLOGY

In this research, a quantitative design was adopted to analyze the impact of AI technology on CBEC export performance by means of a questionnaire survey. The data analysis was carried out using SPSS 29.0 and AMOS 24.0.

3.1 Research Design and Protocol

This study used a quantitative, cross-sectional survey design to examine how four AI-related factors affected the export performance of CBEC enterprises. These factors were insufficient technological adaptability, insufficient AI integration in SCM, talent gap, and market competition pressure. The unit of analysis was the enterprise, and questionnaires were completed by employees at different levels within CBEC enterprises. The research protocol covered questionnaire development and pilot testing, formal data collection, data screening, and statistical analysis. The questionnaire was first refined through expert review and a pilot test with 67 respondents, then distributed online through Questionnaire Star. After data screening, 469 valid responses were retained. The measurement model was evaluated using confirmatory factor analysis in AMOS 24.0, and the hypotheses were tested through multiple regression in SPSS 29.0.

3.2 Population, Sampling, and Data Collection

This section focuses on data collection, which forms the foundation of the entire study. The study subjects, sampling methods, study area, and sample

s are explained here.

3.2.1 Population and sampling

The survey covered enterprises in Chinese CBEC industry that have already adopted AI. However, these enterprises vary significantly in size, industry type, and export volume. Convenience sampling was used, combined with a snowballing approach. The questionnaire was primarily distributed through WeChat groups, corporate communities, and RedNote, with some friends also helping to forward it.

3.2.2 Study location

This survey targeted enterprises engaged in CBEC, primarily chosen because China is indeed at the forefront of digital technology [13]. The survey covered Fujian, Guangdong, Zhejiang, Shanghai, and Beijing, regions with mature logistics systems and numerous pilot demonstration zones and technology innovation centers [6]. This regional selection approach ensures coverage of large and small businesses, and various business models, resulting in a more representative sample. Data collection utilized the Questionnaire Star platform, which has nationwide reach and is not limited by geographical location [14].

3.2.3 Sample size

To ensure the reliability of the statistical analysis, approximately 10 to 15 samples are required for each measurement item [15]. The questionnaire in this study contains 25 measurement items, therefore the minimum required sample size is between 250

and 375. By applying snowball and convenience sampling strategies, 469 valid questionnaires were gathered. This satisfied the “item-sample ratio” principle and provided sufficient power for multiple regression analysis as well as hypothesis testing.

3.3 Variable Measurement and Instrument Development

This section describes the questionnaire design, pilot tests, data preprocessing, and variable coding. A 5-point Likert scale was used for the questionnaire, and then continuously adjusted it through pilot test, data cleaning, and coding, with the aim of making the measurement results more reliable and the data quality higher.

3.3.1 Questionnaire design

The questionnaire collected demographic information and core measurement items. A 5-point Likert scale was used, ranging from “strongly disagree” (1 point) to “strongly agree” (5 point). New items were developed for all five constructs, drawing on the technology readiness and TOE literature [9], [16], studies on AI applications in CBEC supply chains (Tang et al., 2023), research on AI skills and human capital [7], [11], and earlier work on export performance in the CBEC context [6]. Five CBEC practitioners reviewed the drafted items for clarity and relevance, and a pilot test involving 67 respondents helped us further refine the wording. The final measurement items are listed in Table 1.

Table 1: Core Measurement Items

Constructs	Code	Items
Insufficient Technological Adaptability	ITA	ITA1. Our company's existing technical infrastructure is fully capable of supporting artificial intelligence applications. ITA2. Insufficient technological adaptability affects the integration of artificial intelligence technology in the company. ITA3. Our company faces challenges in technology upgrades and maintenance. ITA4. Lack of technological adaptability leads to delays in the implementation of artificial intelligence projects. ITA5. Our company needs more technical support to improve the effectiveness of artificial intelligence technology applications.
Insufficient AI Integration in SCM	AISCM	AISCM1. Our company has failed to fully integrate AI technology in supply chain management, which has affected export efficiency. AISCM2. Insufficient AI integration in supply chain management has limited our ability to optimize inventory in the international market. AISCM3. The company has enough AI support in logistics to reduce export delivery time. AISCM4. Insufficient AI integration in supply chain management reduces the accuracy of demand forecasts. AISCM5. Insufficient AI integration in supply chain management has weakened our relative competitiveness in cross-border e-commerce.
Talent Gap	TG	TG1. Our company is short of professionals in the field of artificial intelligence. TG2. The talent gap limits the application and development of artificial intelligence technology in our company. TG3. Companies struggle to find employees with AI-related skills in the external recruitment market. TG4. Our company's innovation in artificial intelligence technology is not

		restricted by talent shortage. TG5. Our company needs more training to enhance the artificial intelligence skills of our employees.
Market Competitive Pressure	MCP	MCP1. Competitors' application of artificial intelligence technology puts pressure on our company. MCP2. Market competitive pressure prompts our company to accelerate the development of artificial intelligence technology. MCP3. Our company does not need to rely on artificial intelligence technology to remain competitive in the market. MCP4. Competitors' artificial intelligence technology affects our company's market share. MCP5. The company is actively applying artificial intelligence technology to cope with market competition.
CBEC Export Performance	CBECexp	CBECexp1. The application of artificial intelligence technology has increased our company's export sales. CBECexp2. Artificial intelligence technology helps us more accurately predict the demand of the export market. CBECexp3. Artificial intelligence technology has not significantly improved the export efficiency of our supply chain management. CBECexp4. Artificial intelligence technology enables us to respond more quickly to changes in the international market. CBECexp5. Artificial intelligence technology has strengthened the international competitiveness of our products.

3.3.2 Pilot test

To improve the reliability and validity of the questionnaire, this study conducted a pilot test before formal data collection. Personnel from CBEC enterprises (covering different sizes and regions) were selected to participate in the test, and 67 samples were included in the final pilot test analysis. The reliability analysis indicated that the overall Cronbach's α coefficient was 0.972, and each dimension coefficients ranged from 0.852 to 0.879. Validity analysis was verified by the KMO statistic of 0.924 and the highly significant Bartlett test result ($p < 0.001$). Exploratory factor analysis extracted five principal components, explaining 80.471% of the total variance, with clear factor loading, confirming the robustness of the measurement model. The pilot test was designed to evaluate the clarity, logic, and completion time of the questionnaire, with a focus on checking whether the wording of the questions was ambiguous. Based on the feedback, some question expressions were optimized, such as shortening demographic variable names to facilitate respondents' reading and subsequent data variable naming, and changing "AI technology significantly improves export efficiency" to "the degree to which AI technology improves export efficiency" to reduce subjective bias.

3.3.3 Data preprocessing and variable coding

Before the formal analysis, the 506 raw data were cleaned using SPSS 29.0. After removing 37 invalid responses, 469 valid questionnaires were retained for data analysis. Any case with more than 20% missing answers was simply dropped. For variables with less than 5% missing data, mean imputation was used. That way most of the sample could be kept [15]. The data were also checked for

careless responses, such as straight lining or finishing the survey too quickly. Those questionnaires were removed too, just to make sure the remaining data was solid.

Reverse coding items were recalibrated from "strongly agree" (1 point) to "strongly disagree" (5 points). Categorical variables such as company size and export volume were converted to numerical data through dummy coding [17]. Outliers were detected by the interquartile range (IQR) method, confirming that the data distribution met the normality assumption [18].

3.4 Data Analysis Methods

In this study, all data were systematically organized and checked using the SPSS 29.0 and AMOS24.0. First, descriptive statistical analysis was conducted to examine sample statistics and data distribution. Second, the stability of items was examined by Cronbach's α coefficient, and the rationality of the variable dimensions was verified by exploratory factor analysis. Then confirmatory factor analysis was carried out to test the convergent validity and discriminant validity of the measurement model. Finally, multiple regression analysis was performed to clarify the specific mechanism of the independent variable on the dependent variable and verify the rationality and significance of the research hypotheses.

3.4.1 Descriptive statistical analysis

The preliminary analysis included descriptive statistics, outlining the basic characteristics of the data through frequency, percentage, mean, and standard deviation. Charts and tables were used to show the export performance of CBEC enterprises, as well as the distribution of insufficient technological adaptability, insufficient AI

integration in SCM, talent gap, and market competition pressure.

3.4.2 Reliability and validity

The questionnaire was optimized through a pilot test with 67 practitioners to ensure that the questions were clear and consistent with the target structure. In the formal survey, Cronbach's α values were first calculated for key dimensions to ensure the scientific nature of the research tool and the credibility of the research results [19]. Then, the KMO (Kaiser-Meyer-Olkin) test and Bartlett's sphericity test were used to verify the applicability of the data and the validity of factor analysis [20]. Based on the TOE framework, this study used the formal 469 samples to test convergent validity and discriminant validity, confirming the independence and accuracy of the constructs [21].

3.4.3 Multiple regression analysis

After the previous step, a multiple regression analysis was conducted using SPSS 29.0. This method can evaluate the relationship between two or more independent variables (IV) and the dependent variable (DV), quantify the independent impact of the IV on the DV, and determine which IV have a significant impact on the export performance of CBEC enterprises. The R^2 value of the model indicates how much variability of the DV the model explains. The adjusted R^2 value reflects on the number of variables in the model, and this analysis result can provide corresponding strategic recommendations for enterprises [22]. The form of the regression model is as follows, and the specific degree of impact is reflected by the regression coefficient β , which provides data support and strategic guidance for CBEC companies to optimize resource allocation and improve export performance [23].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$$

Where X_1 to X_4 represent insufficient technological adaptability, insufficient AI integration in SCM, talent gap, and market competition pressure.

3.5 Ethics Considerations

This study adhered to ethical guidelines, protected the privacy of participants, and ensured the fairness of the research. Participation was entirely voluntary and participants were aware of the nature, purpose, and process of the research in advance. They could withdraw at any time without any impact.

The information provided by participants was also kept confidential, their privacy and data security were protected, and all data were

anonymized to prevent identification. The study also ensured respect for participants' privacy and that their contributions were used in a secure and responsible manner.

4. RESULTS

This chapter is based on 469 valid questionnaires collected from a formal survey. SPSS 29.0 was used to perform descriptive statistical analysis and reliability tests, and AMOS 24.0 was used to conduct confirmatory factor analysis to assess validity. On this basis, SPSS 29.0 was then used to carry out multiple linear regression analysis to test the relationships between CBEC export performance and the independent variables of insufficient technological adaptability, insufficient AI integration in SCM, talent gap, and market competition pressure. These analyses provide data support and a strategic reference for improving the export performance of CBEC enterprises.

4.1 Descriptive Statistical Analysis

The demographic characteristics of the 469 samples are presented in Table 2. Males accounted for 55.9% ($n = 262$) and females accounted for 44.1% ($n = 207$), with a mean of 1.44 ($SD = 0.497$). Regarding age, the largest groups were 36-45 (40.5%, $n = 190$), and 26-35 years (29.9%, $n = 140$), with a mean of 3.03 ($SD = 0.884$). Regarding education level, over half of the respondents had a bachelor's degree ($n = 247$), accounting for 52.7%. While only one person had a high school degree or below, accounting for 0.2%, the average education level score was 2.99 ($SD = 0.805$). For company positions, 40.1% were senior employees ($n = 188$). Regarding company size, 24.3% had 201-500 employees ($n = 114$). Industry experience was primarily 5-10 years (34.1%, $n = 160$), and 28.1% of enterprises reported annual exports between CNY 10 million and 30 million ($n = 132$).

Table 2: Descriptive Statistics ($N = 469$)

Category	Characteristics	Frequency	Percentage (%)	Mean	Std. Deviation
Gender	Male	262	55.9	1.44	0.497
	Female	207	44.1		
Age	18-25 years	3	0.6	3.03	0.884
	26-35 years	140	29.9		
	36-45 years	190	40.5		
	46-55 years	110	23.5		
	> 55 years	26	5.5		
Highest Education	High School and Below	1	0.2	2.99	0.805
	Diploma	125	26.7		
	Bachelor's Degree	247	52.7		
	Master's Degree	70	14.9		
	PHD and Above	26	5.5		
Company Position	Junior Staff	70	14.9	2.50	0.895
	Mid-level Staff	152	32.4		
	Senior Staff	188	40.1		
	Senior Management	59	12.6		
Company Size (Number of Employees)	1-50 people	52	11.1	3.22	1.250
	51-200 people	88	18.8		
	201-500 people	114	24.3		
	501-1000 people	134	28.6		
	> 1000 people	81	17.3		
Years of Experience in the CBEC Industry	< 1 year	12	2.6	3.49	1.003
	1-3 years	63	13.4		
	3-5 years	156	33.3		
	5-10 years	160	34.1		
	> 10 years	78	16.6		
The Company's Export Amount Last Year	< CNY 1000000	52	11.1	3.18	1.276
	CNY 1000000- CNY 5000000	109	23.2		
	CNY 5000000- CNY 10000000	94	20.0		
	CNY 10000000- CNY 50000000	132	28.1		
	> CNY 50000000	82	17.5		

4.2 Reliability Test

As shown in Table 3, the Cronbach's α coefficients for the five variables range from 0.963 to 0.967, and the total scale's α is 0.713, which exceeds the reliability threshold of 0.7, indicating high internal consistency across the 25 items. The results demonstrate that the scale is reliable for further analysis.

Table 3: Reliability Statistics

Variables	Cronbach's α	No. of items
ITA	0.963	5
AISCM	0.964	5
TG	0.966	5
MCP	0.967	5

CBECexp	0.964	5
Total scale	0.713	25

4.3 Validity Analysis

This study first confirmed that the data were suitable for factor analysis through the KMO and Bartlett's sphericity test, and then used exploratory factor analysis (EFA) to initially explore the structural dimensions of the scale. On this basis, confirmatory factor analysis (CFA) was used to formally evaluate the construct validity, including convergent validity and discriminant validity.

4.3.1 KMO and Bartlett's Sphericity test

Table 4 reports that the KMO value is 0.922 > 0.6, and $p < 0.001$, indicating that the correlation between variables is significant, so the data are suitable for exploratory factor analysis.

Table 4: KMO and Bartlett's Sphericity Test

Test	Value	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.922
Bartlett's Test of Sphericity	Approx. Chi-Square	14274.037
	df	300
	Sig.	< 0.001

4.3.2 Exploratory factor analysis

The Harman single-factor test showed that the first unrotated factor accounted for 27.32% of the total variance, which is below the 40% threshold. This indicates that common method bias is not a serious concern in this study [24]. Results in Table 5 indicate that five principal components were extracted, consistent with the preset dimensions. The cumulative variance explained by these components is 87.792%, exceeding the 60% threshold, with all eigenvalues greater than 1. This indicates that the extracted components capture the primary variation of the data and are representative of the selected factors.

Table 5: Total Variance Explained

Items	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.830	27.320	27.320	6.830	27.320	27.320	4.441	17.765	17.765
2	4.759	19.037	46.357	4.759	19.037	46.357	4.435	17.738	35.504
3	4.249	16.997	63.354	4.249	16.997	63.354	4.392	17.569	53.073
4	4.050	16.200	79.554	4.050	16.200	79.554	4.382	17.527	70.600
5	2.060	8.238	87.792	2.060	8.238	87.792	4.298	17.192	87.792
6	0.227	0.908	88.700						
7	0.208	0.831	89.531						
8	0.198	0.792	90.323						
9	0.193	0.770	91.094						
10	0.187	0.750	91.843						
11	0.175	0.699	92.542						
12	0.168	0.672	93.214						
13	0.161	0.643	93.858						
14	0.157	0.628	94.485						
15	0.154	0.615	95.101						
16	0.146	0.583	95.684						
17	0.139	0.557	96.242						
18	0.136	0.543	96.785						
19	0.131	0.526	97.311						
20	0.126	0.505	97.815						

21	0.125	0.500	98.315						
22	0.114	0.458	98.773						
23	0.110	0.438	99.211						
24	0.101	0.405	99.616						
25	0.096	0.384	100						

Note: Extraction Method: Principal Component Analysis.

As presented in Table 6, the rotated factor loading matrix uses the principal component analysis method to extract factors, with rotation based on Varimax and Kaiser normalization; it converges after 5 iterations. In this matrix, the loadings of the 25 items in the five dimensions of (ITA, AISC, TG, MCP, and CBECexp) on their corresponding factors range from 0.880 to 0.942, all exceeding the commonly used acceptance standard of 0.4, which verifies robustness of the factor structure [25]. None of the 25 items showed obvious cross-loadings on other non-corresponding factors. The five factor structures are well differentiated and can enter the subsequent confirmatory factor analysis stage.

Table 6: Rotated Factor Loading Matrix

Items	F1	F2	F3	F4	F5
ITA1				0.915	
ITA2				0.928	
ITA3				0.922	
ITA4				0.929	
ITA5				0.932	
AISC1			0.928		
AISC2			0.935		
AISC3			0.922		
AISC4			0.931		
AISC5			0.920		
TG1		0.920			
TG2		0.923			

TG3		0.927			
TG4		0.926			
TG5		0.932			
MCP1	0.926				
MCP2	0.927				
MCP3	0.936				
MCP4	0.931				
MCP5	0.942				
CBEExp1					0.897
CBEExp2					0.887
CBEExp3					0.897
CBEExp4					0.880
CBEExp5					0.903

Note: Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

4.3.3 Confirmatory factor analysis

Using AMOS 24.0, confirmatory factor analysis was conducted to assess convergent validity. The standardized factor loadings for the five latent variables in Table 7 range from 0.898 to 0.944, all above 0.7. The average variance extracted (AVE) for each latent variable ranges from 0.840 to 0.854, exceeding the threshold of 0.5. The composite reliability (CR) ranges from 0.963 to 0.967, well above 0.7. These results suggest that the five measurement items corresponding to each latent variable have strong internal consistency and converge well onto the same construct, thus demonstrating convergent validity.

Table 7: Convergent Validity (N = 469)

Latent Variable	Observed Variable	Factor Loading	CR	AVE
Insufficient Technological Adaptability (ITA)	ITA1	0.905	0.963	0.840
Insufficient Technological Adaptability (ITA)	ITA2	0.925		
Insufficient Technological Adaptability (ITA)	ITA3	0.909		
Insufficient Technological Adaptability (ITA)	ITA4	0.921		
Insufficient Technological Adaptability (ITA)	ITA5	0.922		
Insufficient AI Integration in SCM (AISC)	AISC1	0.921	0.964	0.842
Insufficient AI Integration in SCM (AISC)	AISC2	0.925		
Insufficient AI Integration in SCM (AISC)	AISC3	0.905		
Insufficient AI Integration in SCM (AISC)	AISC4	0.927		
Insufficient AI Integration in SCM (AISC)	AISC5	0.910		

Talent Gap (TG)	TG1	0.915	0.966	0.851
Talent Gap (TG)	TG2	0.914		
Talent Gap (TG)	TG3	0.923		
Talent Gap (TG)	TG4	0.929		
Talent Gap (TG)	TG5	0.932		
Market Competition Pressure (MCP)	MCP1	0.909	0.967	0.854
Market Competition Pressure (MCP)	MCP2	0.915		
Market Competition Pressure (MCP)	MCP3	0.926		
Market Competition Pressure (MCP)	MCP4	0.925		
Market Competition Pressure (MCP)	MCP5	0.944		
CBEC Export Performance (CBECexp)	CBECexp1	0.933	0.964	0.842
CBEC Export Performance (CBECexp)	CBECexp2	0.898		
CBEC Export Performance (CBECexp)	CBECexp3	0.905		
CBEC Export Performance (CBECexp)	CBECexp4	0.910		
CBEC Export Performance (CBECexp)	CBECexp5	0.940		

Table 8 presents the discriminant validity results. The diagonal presents the square roots of AVE for each latent variable, ranging from 0.917 to 0.924. Off-diagonal entries are the correlations between latent variables. The absolute correlations between ITA, AISCM, TG and MCP range from 0.002 to 0.067 and are not significant, the four independent

variables share almost no linear overlap. CBEC export performance correlates with ITA, AISCM, TG at -0.263, -0.270, and -0.328 respectively, and with MCP at 0.260, all significant at $p < 0.001$. For each latent variable, the square root of AVE exceeds its off-diagonal correlations. The constructs are well distinguished from one another.

Table 8: Discriminant Validity

Constructs	ITA	AISCM	TG	MCP	CBECexp
ITA	0.917				
AISCM	0.047	0.918			
TG	-0.062	0.002	0.923		
MCP	-0.067	-0.032	0.004	0.924	
CBECexp	-0.263***	-0.270***	-0.328***	0.260***	0.918

Note: *** $p < 0.001$.

4.4 Hypothesis Test

Multiple linear regression was applied to assess the effects of independent variables, such as insufficient technological adaptation, insufficient AI integration in SCM, talent gap, and market competition pressure on the dependent variable CBEC export performance [17], [26]. Table 9 displays the multiple linear regression results, showing that the model is significant overall ($F = 46.415$, $p < 0.001$), with $R^2 = 0.286$, indicating that the independent variables explain 28.6% of the variation in CBEC export performance, suggesting a modest level of explanatory power. The

regression coefficients showed that insufficient technological adaptation ($\beta = -0.248$, $p < 0.001$), insufficient AI integration in SCM ($\beta = -0.239$, $p < 0.001$), and talent gap ($\beta = -0.333$, $p < 0.001$) had negative effects, while market competition pressure ($\beta = 0.224$, $p < 0.001$) had a positive effect. The DW value was measured at 2.021, indicating that the autocorrelation issue is not significant. Looking at the VIF values, the four variables are 1.010, 1.003, 1.004, and 1.005, all far below the standard threshold of 5, indicating that there is no serious multicollinearity among the variables, and the model as a whole is relatively stable [18].

Table 9: Multiple Linear Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	p	VIF
	B	Std. Error	β			
Constant	4.697	0.247	-	19.000	< 0.001	-
ITA	-0.253	0.040	-0.248	-6.287	< 0.001	1.010
AISCN	-0.245	0.040	-0.239	-6.092	< 0.001	1.003
TG	-0.324	0.038	-0.333	-8.476	< 0.001	1.004
MCP	0.223	0.039	0.224	5.690	< 0.001	1.005
R ²			0.286			
DW			2.021			
F			46.415			
p			<0.001			

Note: a. Predictors: (Constant), MCP, TG, AISCN, ITA.

b. Dependent Variable: CBECexp.

The residual distribution was then examined. As shown in Figure 3, the regression standardized residuals for CBEC export performance roughly follow a normal distribution. The mean is approximately -8.85×10^{-17} and the standard deviation is 0.996. This is further supported by Figure 4, where the data points lie close to the diagonal line, indicating good consistency between the observed and expected cumulative probabilities. These results confirm that the residuals satisfy the normality assumption for the regression model.

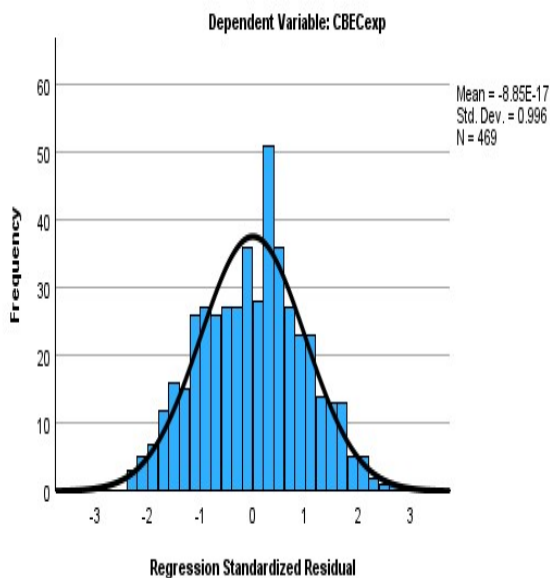


Figure 3: Regression Standardized Residual

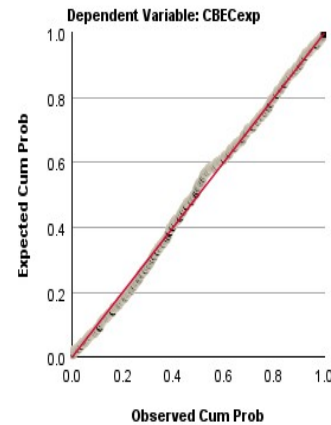


Figure 4: Normal P-P Plot of Regression Standardized Residual

The Figure 5 reveals that the regression standardized residuals are randomly scattered around zero across the range of predicted values, with no obvious funnel shape, residuals falling roughly between -3 and 3, the spread fairly constant, and no extreme outliers present, satisfying the homoscedasticity assumption [18].

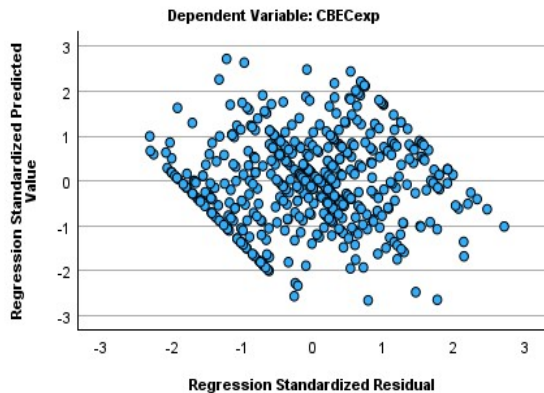


Figure 5: Scatter Plot of Regression Standardized Residual

Based on the regression analysis, the estimated model is formulated as follows:

$$Y = 4.697 - 0.253X_1 - 0.245X_2 - 0.324X_3 + 0.223X_4$$

Where:

Y: CBEC Export Performance

X₁: Insufficient Technological Adaptability (ITA)

X₂: Insufficient AI Integration in SCM (AISC)

X₃: Talent Gap (TG)

X₄: Market Competition Pressure (MCP)

Table 10 provides the hypothesis testing outcomes, all four hypotheses were supported. Insufficient technological adaptability has a significant negative effect on CBEC export performance ($\beta = -0.248$, $p < 0.001$), supporting H1. Insufficient AI integration in SCM has a significant negative effect ($\beta = -0.239$, $p < 0.001$), supporting H2. Talent gap has a significant negative effect ($\beta = -0.333$, $p < 0.001$), supporting H3. Market competition pressure has a significant positive effect ($\beta = 0.224$, $p < 0.001$), supporting H4.

Table 10: Hypothesis Test Results

Hypothesis		Findings	Results
H1	Insufficient technological adaptability has a significant negative influence on the export performance of CBEC enterprises.	$\beta = -0.248$ $p < 0.001$	Accepted
H2	Insufficient AI integration in SCM has a significant negative influence on the export performance of CBEC enterprises.	$\beta = -0.239$ $p < 0.001$	Accepted
H3	The talent gap has a significant negative influence on the export performance of CBEC enterprises.	$\beta = -0.333$ $p < 0.001$	Accepted
H4	Market competition pressure has a significant positive influence on the export performance of CBEC enterprises.	$\beta = 0.224$ $p < 0.001$	Accepted

5. DISCUSSION

This chapter presents the empirical results and discusses the four hypotheses, all of which were supported. It confirms the applicability of the TOE framework in the CBEC context and explains the mechanisms through which technological adaptability, supply chain AI integration, and talent gap exert significant negative effects on export performance, while market competition pressure shows a significant positive effect. The discussion also provides theoretical and practical implications. Based on the findings, management suggestions are proposed in four areas, namely talent development, technological adaptation, AI integration in SCM, and market competition response. This section also analyzes the limitations of the research and points out directions for further investigation.

5.1 Summary of Key Findings

Multiple linear regression analysis was conducted on 469 valid questionnaires using SPSS 29.0. The results showed that insufficient

technological adaptability ($\beta = -0.248$, $p < 0.001$), insufficient AI integration in SCM ($\beta = -0.239$, $p < 0.001$), and talent gap ($\beta = -0.333$, $p < 0.001$) all had significant negative impacts on the export performance of CBEC enterprises, with the talent gap having the largest impact coefficient. Market competition pressure, on the other hand, showed a significant positive effect ($\beta = 0.224$, $p < 0.001$). The more intense the competition, the better the export performance of enterprises. All four hypotheses were supported. It is not easy for AI to truly unleash its value in the cross-border e-commerce field, organizational-level talent gap is the most critical constraint, while the external competitive environment continues to play a significant driving role.

5.2 Comparison with Previous Literature

Compared to previous studies, the present findings largely align. The TOE framework has long stated that technological readiness, IT resources, and organizational capabilities significantly impact enterprise performance [9],

which is consistent with the conclusions; insufficient technological adaptability does indeed drag down export performance. Insufficient AI integration in SCM also negatively impacts delivery reliability and customer satisfaction [2]. IT human capital promotes innovation [11], and enterprises with AI-skilled personnel, especially exporters, experience higher sales [10]. These findings largely coincide with this conclusion that the talent gap has the greatest negative impact. Furthermore, this positive effect is consistent with prior evidence that market competition drives technology adoption and innovation [12], further confirming the positive effect of market competitive pressure.

The main difference in this study is the ranking of influencing factors. The talent gap stands out as the strongest negative factor due to long training cycles and limited supply of composite AI talent [10], [11]. In contrast, technological and supply chain issues can be addressed more easily with external help. This is related to the sample drawn from fast-growing CBEC regions in China, where talent demand is particularly urgent. Unlike many international studies that focus on hardware or use structural equation modeling, this study's cross-sectional regression approach better captures real practical challenges. Moreover, the positive effect of market competition pressure differs from domestic e-commerce research, where excessive competition often harms performance. This highlights market structure as a key boundary condition.

5.3 Mechanism Explanation

Insufficient technological adaptability leads to difficulties in effectively integrating AI algorithms with existing systems, resulting in data silos and hindering the accuracy of demand forecasting and the effectiveness of personalized marketing. Insufficient AI integration in SCM disrupts the synergy between inventory management, logistics operations, and demand forecasting, reducing delivery reliability, increasing return rates, and weakening buyer trust and repurchase intentions. The negative impact of talent gap is most significant, as it not only limits the optimized application of AI models but also further exacerbates difficulties in technological adaptability and supply chain integration, representing the most prominent bottleneck at the organizational level. Conversely, competitive pressure exerts its influence. The more intense the market competition, the more inclined companies are to increase their AI investment, leading to improvements in resource

utilization efficiency and customer experience. These results largely align with the research hypotheses and clearly reveal the operational logic of the TOE framework in AI-driven cross-border trade scenarios.

5.4 Theoretical and Managerial Implications

Theoretically, this study used the TOE framework to analyze the impact of three dimensions, namely technology, organization, and environment, on CBEC export performance. The results showed that the talent gap had the greatest negative impact, even surpassing technology and supply chain issues. This suggests that in a highly uncertain environment such as CBEC, human factors may be more critical than technology infrastructure. Previous studies have mostly focused on technological factors; this study provides a different perspective. Furthermore, while domestic e-commerce research typically considers excessive competition detrimental to performance, this study found that in a fragmented international market, competitive pressure can actually drive performance improvement, indicating that market structure cannot be ignored.

For CBEC enterprises, the most practical approach is to address the AI talent shortage through internal training and university-industry collaborations. In the short term, external AI consultants can also be sought. Technically, there's no need to rush into a complete system overhaul. Modular integration or low-code tools can be used for gradual implementation. Pilot programs with AI vendors can also be implemented first. AI applications in the SCM should not be implemented all at once. Start with demand forecasting and inventory management, then gradually expand to logistics and customer service. Faced with competitive pressure, CBEC enterprises can turn pressure into motivation through competitive intelligence systems and AI tools such as intelligent product selection and automatic translation. From a policy perspective, providing shared AI platforms and technical consulting to enterprises can effectively lower their entry barriers.

5.5 Limitations and Directions for Further Research

Several limitations of this study need attention. Cross-sectional designs inherently struggle to establish causal relationships, and the data derive entirely from firm self-reporting, which raises concerns about the risks of common method bias and societal expectation bias. The model did not

include control variables such as firm size and industry experience, necessitating further testing of the robustness of the results. Given that the sample is entirely from China, caution is required when generalizing to other countries. Even with multiple regression, cross-sectional data still have limited capacity to handle endogeneity issues.

Future research could adopt a longitudinal design to identify causality, replacing self-reporting with objective data such as company records or customs declarations, and incorporating company size and industry experience into the model. Such a design would also allow researchers to explore whether the talent gap remains the main barrier over time and whether competitive pressure has similar effects across different market structures. Expanding the sample CBEC enterprises in other countries would make the conclusions more robust.

6. CONCLUSION

Based on the TOE framework, this study empirically found that insufficient technological adaptability, insufficient AI integration in SCM, and a significant talent gap all constrain the export performance of Chinese CBEC enterprises, while market competition plays a driving role. The study also answered the four questions posed at the beginning, namely internal barriers within enterprises are the main reason why the value of AI is difficult to fully realize, while external competition is a significant driving force.

This study supplements empirical data from Chinese CBEC enterprises to some extent, helping to understand the actual role of AI in CBEC, and also provides some reference directions for the digital transformation of emerging economies. Facing increasingly fierce global digital trade competition, firms that successfully overcome talent bottlenecks, achieve deeper AI integration in supply chains, and convert market pressure into innovation will be in a stronger position to improve their export performance and international competitiveness.

Looking ahead, enterprises should focus more on talent development and digital supply chain collaboration. Governments and industry organizations also need to create better supporting conditions through policy measures and resource-sharing platforms. This study offers an empirically grounded reflection on the high-quality development of Chinese CBEC enterprises in the AI era, and it is hoped that future research will continue to explore these issues in greater depth.

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