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Smart City Construction, Artificial Intelligence Development, and the Quality of Export Products: A Study Based on Micro-Level Data of Chinese Enterprises

Jiayu Ou [1,2], Zhiqiang Zheng [3,*], Xiaojing Ou [4,*] and Naili Zhang [5]

[1] Postdoctoral Mobile Station of Applied Economics, Zhongnan University of Economics and Law, Wuhan 430073, China; oujiayu268@foxmail.com
[2] Guangxi Beibu Gulf Bank Postdoctoral Programme, Nanning 530200, China
[3] Business School, Finance Research Institute, University of Jinan, Jinan 250100, China
[4] School of Economics, Guangxi Minzu University, Nanning 530006, China
[5] School of Economics, Shandong University, Jinan 250100, China; naili@sdu.edu.cn
* Correspondence: sm_zhengzq@ujn.edu.cn (Z.Z.); ouxiaojing168@foxmail.com (X.O.); Tel.: +86-132-9033-8504 (Z.Z.); +86-156-7700-8815 (X.O.)

Abstract: Quality improvement is essential for a nation's economy to transition from large to strong. In the 21st century, a new wave of quality development has emerged globally, and upgrading the quality of enterprise export products is a key measure for driving exports and supporting high-quality economic development. The development of artificial intelligence, as the new core engine driving technological revolution and industrial transformation, will profoundly alter various aspects of economic activities, including production, distribution, exchange, and consumption. Exploring and cultivating new artificial intelligence-driven momentum to enhance the quality of enterprise export products is inevitably a major theoretical and practical issue of common interest to governments, enterprises, and academia. This paper uses China, a major developing and export-oriented economy, as a case study to explore the policy measures for stimulating new momentum in artificial intelligence development and their effects and transmission mechanisms on improving the quality of enterprise export products. Specifically, it constructs a theoretical model to examine the relationship between smart city construction, artificial intelligence development, and the quality of enterprise export products. By considering the smart city construction projects launched by the Chinese government as a quasi-natural experiment to facilitate artificial intelligence development, the study employs matched city-enterprise data from 2007 to 2015 and utilizes a difference-in-differences (DID) methodology to empirically test the impact of smart city construction on enhancing the quality of enterprise export products. According to the study, the policy-driven nature of smart city construction significantly enhances the quality of enterprise export products. This beneficial impact is particularly evident in the eastern regions, as well as in labor-intensive and capital-intensive industries, and among foreign-invested and private enterprises. Mechanism tests and additional analyses indicate that artificial intelligence development is significantly more advanced in smart cities than in non-smart cities, with the gap between them steadily widening. The construction of smart cities significantly advances artificial intelligence development, which subsequently enhances the quality of enterprise export products. Furthermore, smart cities can substantially contribute to this improvement by facilitating a more efficient, market-oriented allocation of resources.

Keywords: smart city construction; quasi-natural experiment; artificial intelligence; quality of enterprise export products

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1. Introduction

Since 1978, when the Reform and Opening-up policy was introduced, there has been a notable increase in China's merchandise trade. Nevertheless, the quality of its products

remains significantly behind that of global leaders, resulting in a notable disparity with major trading nations [1]. Amidst the new wave of quality development in the 21st century, improving the quality of enterprise export products is an essential strategy for achieving high-quality economic development in China. For China to advance economically with high-quality development, enhancing the quality of enterprise export products is imperative. With the rapid progression of the artificial intelligence technological revolution, developed economies such as the European Union, Germany, the United States, and Japan are swiftly advancing their artificial intelligence development strategies. For instance, the European Union has introduced the "White Paper on Artificial Intelligence", Germany has implemented the "Industry 4.0" strategy, Japan has launched the "New Robot Strategy", and the United States has rolled out the "National Artificial Intelligence Research and Development Strategic Plan". Similarly, China has escalated its artificial intelligence efforts with initiatives such as the "New Generation Artificial Intelligence Development Plan" and the "Three-Year Action Plan for Promoting the Development of a New Generation of Artificial Intelligence Industry (2018–2020)", thereby elevating artificial intelligence development to a national strategic priority [2,3]. Data reveal that by 2018, China's artificial intelligence development had achieved a significant scale, with Chinese industrial robots accounting for 35.61% of global new installations and 25.35% of the total stock, consistently ranking first worldwide in terms of installed units [4]. China has explicitly identified artificial intelligence as a crucial new engine for growth. In this context, it is essential to explore how AI-driven mechanisms can be developed to enhance the quality of enterprise export products and to identify key policy priorities for further research.

As intelligent technologies such as industrial robots, big data, and cloud computing advance rapidly, governments worldwide are placing increasing emphasis on the practical implementation of smart city projects. For example, the South Korean government proposed the "U-Korea" development strategy in 2004, with the goal of building digital smart cities; the European Union advanced the European Smart Cities Network Plan in 2006; the Japanese government launched the "I-Japan" strategy in 2009, integrating e-government, healthcare, education, and other sectors into a comprehensive smart city framework; and the United States initiated its first smart city project in Dubuque in 2009 [5]. Similarly, the Chinese government launched national smart city pilot projects in 2012, 2013, and 2014. By 2015, more than 85% of Chinese cities were actively promoting smart city initiatives, with over 300 pilot projects underway. Developing cities that are livable, resilient, and smart continues to be a key direction in China's efforts toward urban modernization [6]. The essence of smart city construction is the application of next-generation technologies to integrate diverse urban facets—such as people, administrative functions, and transportation—moving toward a more interconnected, IoT-driven, and intelligent urban environment. This approach aims to promote efficient urban operations through comprehensive sensing, deep integration, and intelligent coordination, which in turn creates favorable conditions for urban enterprises and boosts the overall quality of life for residents. Therefore, this paper aims to explore whether smart city construction can act as a policy lever for advancing artificial intelligence, whether it exerts a policy-driven effect on enhancing the quality of enterprise export products, and whether the promotion of artificial intelligence serves as a policy transmission mechanism through which smart city construction aids in improving the quality of export products.

2. Literature Review

This study aims to explore the impact of smart city construction, through the transmission mechanisms of artificial intelligence, on enhancing the quality of enterprise export products. To frame the study, three strands of the literature that closely align with the research topic are reviewed, with the potential mechanism serving as the focal point for analysis. First, it reviews studies on the policy impacts of smart city construction. Second, it synthesizes research on how artificial intelligence development affects the quality of enterprise export products. Third, it presents a detailed examination of methods used

to evaluate artificial intelligence development. By examining these sources, we gain insight into the cutting-edge research development related to the substantial policy impact embedded in smart city construction. It also helps understand the effects of artificial intelligence on improving the quality of enterprise export products and the measurement of relevant indicators. This groundwork clarifies existing research limitations and areas for improvement, setting the stage for identifying potential innovative directions in this study. Specifically:

First, the policy effects on the evaluation of smart city construction. Some scholars have examined the macroeconomic impacts of smart city construction, finding that they help reduce regional environmental pollution [7], accelerate technological innovation [8], upgrade industrial structures, narrow regional economic and urban–rural income disparities [9], and promote high-quality economic growth [10]. Some studies from a micro-enterprise perspective indicate that smart city construction enhances overall productivity [11], promotes digital transformation [12], and stimulates innovation within enterprises [13]. For instance, Wang et al. (2022) found, based on data from Chinese prefecture-level cities and listed companies, that smart city construction helps lower transaction costs for firms, thereby enhancing total factor productivity [14]. Jiang et al. (2021) discovered that smart city construction addresses constraints in talent and capital for digital transformation through effects related to human capital accumulation and technological capital [11]. Additionally, some studies focus on the impact of smart city construction on international trade. For instance, Ye et al. (2021) found that smart city construction significantly expands the scope of foreign direct investment (FDI) by reducing investment costs, enhancing infrastructure, and improving population quality [15]. Jayathilaka and Park (2022) indicated that smart city construction significantly promotes FDI by improving the business environment and driving technological innovation [16]. Li (2024) demonstrated that smart city construction can significantly enhance city export volumes through effects related to information costs, resource allocation, and technological innovation [17].

Second, the impact of artificial intelligence development on the quality of enterprise export products. Several studies have examined the effects of artificial intelligence development on export product quality from different perspectives. At the regional level, Hong et al. (2022) constructed indicators of industrial robot application at the provincial level in China using data from the IFR Industrial Robots Database [18]. They found that the industrial robot application has a U-shaped effect on the upgrading of export product quality. Shahzad et al. (2022) discovered that artificial intelligence significantly promotes the enhancement of export product quality for Chinese enterprises [19]. At the industry level, Lin et al. (2022) used data from the IFR Industrial Robots Database to construct industry-level artificial intelligence measurement indicators and found that artificial intelligence significantly supports the improvement of export product quality for Chinese enterprises [20]. DeStefano and Timmis (2024) developed industry-level indicators of industrial robot application and empirically demonstrated that industrial robots significantly improve export product quality, with a more pronounced effect in developing economies compared to developed ones [21]. At the enterprise level, Lu et al. (2024) used data from the China Customs Trade Database to construct enterprise-level indicators of industrial robot application [22]. They found that industrial robots significantly enhance the quality of Chinese export products by improving labor productivity and human capital, with a dynamic effect where the impact first increases and then decreases. Xu and Tian (2023) used text information from annual reports of Chinese listed companies to build an enterprise-level artificial intelligence indicator [23]. Their study revealed that artificial intelligence significantly positively impacts the quality of export products through channels such as optimizing resource allocation efficiency and enhancing information processing capabilities.

Third, the measurement studies of artificial intelligence development. The integration of artificial intelligence development with various industries presents significant challenges in data collection. Currently, there is no unified standard for measurement, and existing

research mainly uses single indicators or composite indicators for measurement. On the single indicator side, most studies use data from the IFR Industrial Robots Database to construct regional or industry-level artificial intelligence development indicators, such as regional industrial robot penetration (Acemoglu and Restrepo, 2020) [24] and industry-level industrial robot application density (Graetz and Michaels, 2018) [25]. Some research uses customs trade data to determine whether firms import core components of industrial robots and in what quantities (Acemoglu et al., 2020; Fan et al., 2021) [26,27]. Other studies attempt to measure artificial intelligence through specific branches, such as artificial intelligence patents, keyword frequencies in annual reports, or enterprise survey data (Giczy et al., 2022) [28]. Composite indicators are used in research focusing on national or regional artificial intelligence development levels. For instance, Mikalef and Gupta (2021) measured artificial intelligence development in six leading global economies based on environmental support, knowledge creation, and industrial competitiveness [29]. Li et al. (2017) assessed the degree of industrial intelligence in Chinese provinces from perspectives such as infrastructure, production application, competitiveness, and benefits [30]. Lin and Xu (2024) evaluated the level of industrial intelligence in Chinese prefecture-level cities based on intelligent conditions, applications, and technologies [31]. Studies typically measure artificial intelligence development using either single indicators, such as specific branches like industrial robot applications [32], or comprehensive indicators [33]. Earlier works evaluated provincial-level industrial intelligence in China based on dimensions such as infrastructure, production applications, competitiveness, and efficiency [34]. Other scholars measured the industrial intelligence of Chinese prefecture-level cities across dimensions of intelligent conditions, applications, and technologies.

The literature review reveals that while there is substantial research on the macroeconomic impacts of smart city construction and the effects of artificial intelligence on export product quality, there is limited focus on how smart city initiatives specifically influence export product quality. Additionally, although many studies measure artificial intelligence development, they often rely on single indicators, which can introduce measurement errors. Research employing composite indicators to assess artificial intelligence development at the city level is still relatively rare, as previous studies have been constrained by data availability and often used provincial-level data as proxies. Through the review of the literature, several key observations emerge: Firstly, research has extensively covered the macroeconomic effects of smart city construction, and some studies have started examining its implications for micro-level businesses. However, given that export product quality is essential for the high-quality economic advancement of urban areas in modern China, there is a notable absence of studies focusing on how smart city construction impacts the quality of export products from enterprises and the mechanisms involved. Secondly, while the effects of artificial intelligence on enterprise export product quality have been extensively studied, there is a noticeable gap in the literature regarding the influence of government policies on artificial intelligence development. Specifically, there is a scarcity of research on how such policies impact export product quality through the pathways of artificial intelligence development. Thirdly, although numerous studies have assessed artificial intelligence development, most rely on single indicators, which can lead to measurement biases. Comprehensive indicators for assessing artificial intelligence development, especially at the city level, are relatively rare. Some prior research has made some attempts in this direction, but due to data availability constraints, some indicators were still derived from provincial-level data.

Summarizing the findings, the main marginal contributions of this paper are as follows: (1) Research Perspective. By utilizing smart city construction as a quasi-natural experiment for advancing artificial intelligence, this research assesses how such construction impacts the quality of export products and the mechanisms at play. This research advances the field by extending the current understanding of smart city policy impacts, offering new insights into its effects on micro-enterprises, and contributing to theoretical frameworks on artificial intelligence policy and quality-driven economic development.

(2) Theoretical Analysis. This study incorporates artificial intelligence development into the enterprise product quality model and theoretically analyzes both the direct and indirect mechanisms through which smart city construction affects micro-enterprises. It provides a theoretical framework for understanding the micro-policy effects of smart city construction. (3) Empirical Examination. The paper attempts to construct a comprehensive indicator for measuring artificial intelligence development in cities, offering valuable insights and supplements to artificial intelligence development assessment studies. By comparing the artificial intelligence development characteristics between smart and non-smart cities, the study verifies whether artificial intelligence development serves as a policy transmission mechanism through which smart city construction enhances the quality of enterprise export products. Additionally, it delves deeper into the effects of smart city construction on the quality of enterprise export products, specifically focusing on the role of market-oriented factor allocation mechanisms. By providing evidence on the micro-level policy effects of smart city construction, this research supports theoretical frameworks and offers practical recommendations for utilizing artificial intelligence to boost the quality of enterprise export products.

3. Theoretical Model and Mechanism Analysis

In this section, we explore the theoretical mechanisms through which smart city construction influences the quality of enterprise export products. Building upon the research of Hallak and Sivadasan (2013), this paper integrates artificial intelligence development into the enterprise product quality model [35]. By conceptualizing artificial intelligence development as a key influencing pathway, this section reveals the fundamental mechanisms through which smart city construction impacts the quality of enterprise export products. This also provides a theoretical basis for subsequent empirical testing.

3.1. Incorporating Artificial Intelligence Development into the Enterprise Product Quality Model

3.1.1. Consumer Behavior

Considering vertical product differentiation, consumers' utility levels are related to product quality and quantity and follow a CES utility function. The problem of consumers maximizing utility under budget constraints can be represented as:

$$\max U = \left[\int_{\omega\in\Omega} (\lambda_\omega q_\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega\right]^{\frac{\sigma}{\sigma-1}} s.t. E = \int_{\omega\in\Omega} p_\omega q_\omega \mathrm{d}\omega \quad (1)$$

In this context, ω represents product variety; Ω denotes the set of available products for selection; λ_ω, q_ω, and p_ω represent the quality, quantity, and price of each product ω respectively; $\sigma > 1$ signifies the elasticity of substitution between different products; and E indicates the consumer's expenditure level. Solving the consumer utility maximization problem yields the demand for products ω as follows:

$$q_\omega = \frac{\lambda_\omega^{\sigma-1} E}{p_\omega^\sigma P} \quad (2)$$

Here, $P \equiv \int_{\omega\in\Omega} \lambda_\omega^{\sigma-1} p_\omega^{1-\sigma} \mathrm{d}\omega$ represents the aggregate price index. According to Equation (2), if the quality of products ω is higher and prices are lower, market demand increases. Due to symmetry among different product varieties, for simplicity, subsequent formulas remove the subscripts representing individual products ω.

3.1.2. Producer Behavior

Based on Hallak and Sivadasan (2013) [35], enterprise heterogeneity arises from the quality productivity φ and quality capacity of enterprises producing goods ξ. Higher values of these parameters indicate that enterprises require fewer variable costs MC and fixed

costs F to produce goods of higher quality λ. Accordingly, this paper sets the enterprise's production cost function as:

$$TC = MC(\lambda, \varphi) + F(\lambda, \xi) = \frac{c\lambda^{\beta}}{\varphi} + \frac{f\lambda^{\alpha}}{\overline{\xi} g(m)^{\theta}} + F_0 \tag{3}$$

where c, f, and F_0 are positive constants; β and α represent the elasticity of marginal cost with respect to quality and the elasticity of fixed costs with respect to quality, respectively; φ denotes enterprise quality productivity heterogeneity, reflecting differences in variable costs among enterprises; $\overline{\xi} g(m)^{\theta}$ signifies quality capacity heterogeneity, characterizing the efficiency of fixed-cost investment for improving product quality within enterprises; $\overline{\xi}$ represents enterprise-specific quality capacity unaffected by factors related to artificial intelligence development; $\theta \in [0, 1)$ indicates diminishing marginal returns to fixed asset investment for enhancing enterprise quality capacity; $g(\cdot)$ is a monotonically increasing function of artificial intelligence development m, $\partial g(m)/\partial m > 0$ with economic intuition suggesting that fostering artificial intelligence development facilitates the creation of a conducive ecosystem for artificial intelligence technology applications and reduces enterprises' entry costs. This prompts enterprises to strategically adjust their production and operational activities promptly, accelerating the adoption of artificial intelligence technology in product development, innovation, production, and sales processes, ultimately enhancing their capacity for high-quality production.

According to Equations (2) and (3), the enterprise's profit function can be derived as follows:

$$\pi = \frac{E}{P} \frac{\lambda^{\sigma-1}}{p^{\sigma}} \left(p - \frac{c\lambda^{\beta}}{\varphi} \right) - \frac{f\lambda^{\alpha}}{\overline{\xi} g(m)^{\theta}} - F_0 \tag{4}$$

In solving the first-order conditions for product price p and product quality λ in Equation (4), we derive the optimal choice of export product quality for enterprises aiming to maximize profit:

$$\lambda^{*} = \left[\frac{(1-\beta)}{\alpha} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \left(\frac{\varphi}{c} \right)^{\sigma-1} \frac{E}{P} \frac{\overline{\xi}}{f} g(m)^{\theta} \right]^{\frac{1}{\alpha-(1-\beta)(\sigma-1)}} \tag{5}$$

Taking the partial derivatives of Equation (5) with respect to enterprise quality productivity φ, quality capacity $\overline{\xi}$, and artificial intelligence development m, we obtain:

$$\frac{\partial \lambda^{*}}{\partial \varphi} = \kappa \left[\frac{(1-\beta)}{\alpha} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \left(\frac{\varphi}{c} \right)^{\sigma-1} \frac{E}{P} \frac{\overline{\xi}}{f} g(m)^{\theta} \right]^{\kappa-1} \frac{(\sigma-1)\varphi^{\sigma-1}}{c^{\sigma-1}} > 0 \tag{6}$$

$$\frac{\partial \lambda^{*}}{\partial \overline{\xi}} = \kappa \left[\frac{(1-\beta)}{\alpha} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \left(\frac{\varphi}{c} \right)^{\sigma-1} \frac{E}{P} \frac{\overline{\xi}}{f} g(m)^{\theta} \right]^{\kappa-1} \frac{1}{f} > 0 \tag{7}$$

$$\frac{\partial \lambda^{*}}{\partial m} = \kappa \left[\frac{(1-\beta)}{\alpha} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \left(\frac{\varphi}{c} \right)^{\sigma-1} \frac{E}{P} \frac{\overline{\xi}}{f} g(m)^{\theta} \right]^{\kappa-1} \theta g(m)^{\theta-1} \frac{\partial g(m)}{\partial m} > 0 \tag{8}$$

where $\kappa = 1/[\alpha - (1-\beta)(\sigma-1)]$. According to Equations (6)–(8), it is evident that, under the condition of maximizing enterprise profit, the optimal choice for export product quality is a monotonically increasing function of enterprise quality productivity, quality production capacity, and artificial intelligence development. Enhancing enterprise quality productivity, quality production capacity, and the level of artificial intelligence development contributes to driving improvements in the quality of exported products.

3.2. Theoretical Mechanisms

Leveraging the mathematical models discussed earlier, this study explores how smart city construction impacts enterprise export product quality by examining both direct and indirect mechanisms.

Direct Impact Mechanism. Leveraging its policy advantages, smart city construction predominantly exerts positive effects on the quality of enterprise export products through three primary channels. Firstly, smart city construction facilitates the reduction in external information acquisition costs for enterprises. Under the impetus of smart city initiatives, urban information infrastructure experiences rapid growth, leading to the widespread adoption of technologies such as networked intelligent communication, e-government services, and Internet search engines. This development reduces the costs associated with business interactions between enterprises, customers, and governmental bodies, while also lowering the information costs related to understanding market supply and demand dynamics and policy environments. The decreased difficulty in accessing data and information helps enterprises dynamically optimize their production structures and enhance productivity levels. Secondly, smart city construction empowers technological innovation within enterprises. Smart city initiatives foster advancements in digital technologies, including cloud computing, big data, the Internet of Things (IoT), blockchain, and smart sensors, offering strong technological support for research and development (R&D) innovation. Externally, smart city construction fosters data integration and sharing via various smart sensors embedded in buildings, power grids, and transportation facilities, weakening the barriers to communication, learning, and knowledge spillovers among innovation entities. This promotes shared, collaborative, and open innovation among urban enterprises. Internally, smart city construction provides enterprises with precise data and information, enabling more scientific and intelligent innovative decision-making and management. Additionally, the reduction in transaction costs resulting from smart city construction motivates enterprises to dedicate more time and resources to research and development, thereby boosting their technological innovation capabilities. Thirdly, smart city construction catalyzes a "siphon effect" on production factors such as labor and capital. By optimizing production and living environments and deepening levels of openness to external influences, smart city initiatives effectively attract a large influx of technical talent and foreign capital into cities. This influx speeds up product R&D activities and improves both the impact and productivity of developing innovative products. Thus, smart city construction enhances enterprise quality productivity and production capacity by reducing information costs, empowering technological innovation, and attracting production factors. According to Equations (6) and (7), enterprise quality productivity and production capacity are crucial parameters for enhancing the quality of export products. Therefore, smart city construction is theoretically expected to significantly enhance export product quality. Based on this analysis, the following hypothesis is proposed.

Indirect impact mechanisms. Equation (8) indicates that advancements in artificial intelligence contribute to improving the quality of enterprise export products. Here, the theoretical framework of how smart city construction fosters the development of artificial intelligence is elucidated from three perspectives: pilot policy objectives, the growth of digital and intelligent industries, and the application of digital technologies by enterprises. Firstly, from the perspective of pilot policy objectives, the enhancement of urban artificial intelligence infrastructure and the promotion of practical applications of artificial intelligence technologies are aimed for by smart city construction. The Chinese government's evaluation of smart cities in the "National Smart City (District, Town) Pilot Indicator System (Trial)" has explicitly outlined key construction areas such as the coverage and access speed of wireless and broadband networks, the informatization of government services such as decision support, information disclosure, and online services, as well as the informatization of basic public services including labor employment, public education, social insurance, and healthcare. Additionally, the system addresses specialized applications such as smart logistics, smart payments, smart finance, smart energy, smart transportation, smart

homes, and smart communities. Pilot regions for smart city construction generally show greater policy support and demand for artificial intelligence than non-pilot areas, thereby inevitably leading to an increase in the level of urban artificial intelligence development. Secondly, smart city construction is expected to drive the rapid expansion and advancement of the digital and intelligent industries. Pilot city governments implement policies such as fiscal subsidies and tax incentives to support the development of "Internet Plus" industries, which rely on crucial information technologies like the Internet of Things, cloud computing, big data, and artificial intelligence, necessary for smart city construction. The rise of high-tech industries subsequently boosts the development of high-end productive services, such as information technology, research and development, financial services, and business services. Furthermore, it drives the growth of consumer-oriented smart industries such as smart homes, e-commerce, remote education, and smart eldercare. Ultimately, this development leads to a "virtuous cycle" of upward progression in urban artificial intelligence. Thirdly, from the perspective of enterprise digital technology applications, smart city construction drives enterprises to accelerate their digital transformation. On one hand, it creates an ecosystem characterized by comprehensive data collection, real-time monitoring, precise delivery, and interactive sharing. This motivates enterprises to actively incorporate artificial intelligence into various business activities, including scenario shaping, flexible production, product quality testing, storage and packaging, transportation and handling, as well as machine maintenance and repair. On the other hand, smart city construction seeks to shift traditional urban development from an extensive model to a more intelligent and refined governance approach. Enterprises that cause significant ecological damage, such as those with high pollution and high energy consumption, will be "compelled" to adopt smart technologies to upgrade their production processes, thereby achieving efficient, precise, and environmentally friendly production. Based on the analysis above, this paper proposes the following hypotheses.

Drawing from the theoretical mechanism analysis presented above (as shown in Figure 1), this paper proposes the following hypotheses:

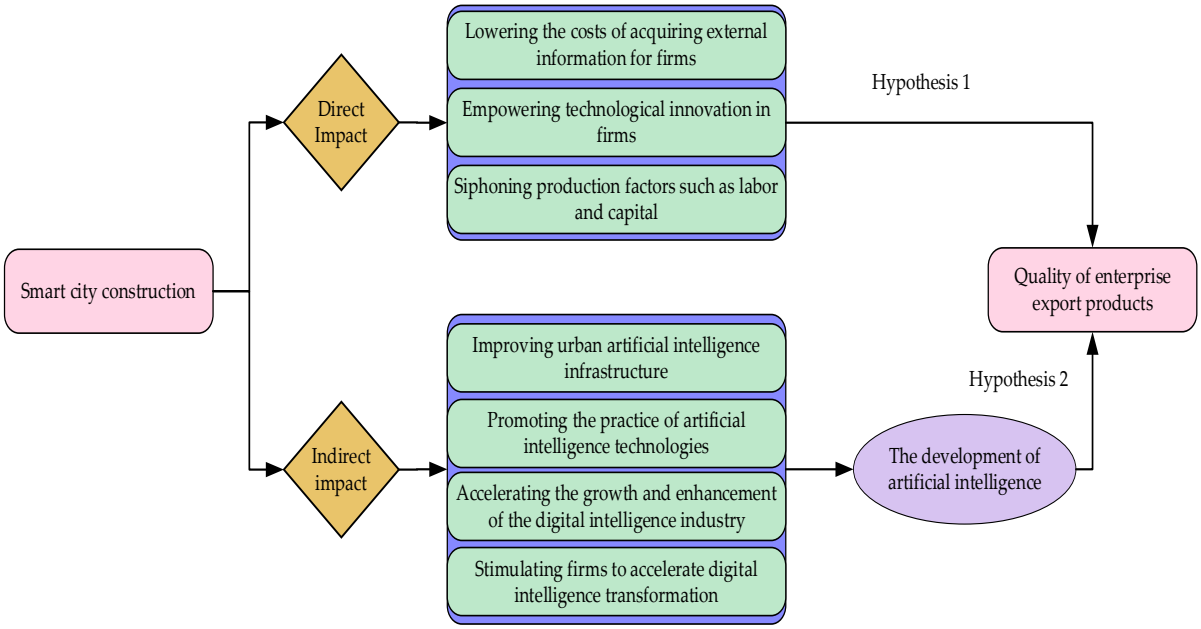


Figure 1. Theoretical Framework for "Smart City Construction—Artificial Intelligence Development—Quality of Enterprise Export Products".

Hypothesis 1. *Improvements in the export product quality of enterprises can be driven by smart city construction.*

Hypothesis 2. *Smart city construction promotes the development of artificial intelligence, which in turn drives improvements in the quality of exported products by enterprises. Thus, fostering artificial intelligence development serves as an indirect mechanism through which smart city initiatives enhance export product quality.*

4. Model Specification, Variable Measurement, and Data Description

4.1. Model Specification

Building on the earlier theoretical analysis, this study uses a Differences-in-Differences (DID) model to investigate the effects of smart city construction on the quality of enterprise export products, focusing on policy-driven impacts and transmission mechanisms. The baseline econometric model is set as follows:

$$lnquality_{cit} = \gamma_0 + \gamma_1 did_{ct} + \sum \gamma_j Control + \mu_i + \nu_t + \varepsilon_{cit} \quad (9)$$

where $lnquality_{cit}$ represents the quality of exported products by urban enterprises in year t; $did_{ct} = treat_c \times post_t$ denotes whether the enterprise is located in a pilot city $treat_c$ for smart city construction and during the pilot period $post_t$; $Control$ represents the vector of control variables with corresponding regression coefficients γ_j; μ_i and ν_t denote individual and year-fixed effects, respectively; ε_{cit} is the error term. γ_1 represents the coefficient of interest in this study, capturing the net effect of smart city construction on the quality of enterprise export products. It is anticipated that $\gamma_1 > 0$ will demonstrate that smart city construction can drive improvements in the quality of exported products by enterprises.

4.2. Variable Measurement

4.2.1. Dependent Variables

The dependent variable in this study is "the quality of enterprise export products", denoted as $lnquality_{cit}$, refers to the weighted average quality of all products exported by enterprise i in city c during year t. Drawing on Khandelwal et al. (2013), the estimation of product quality is derived by incorporating it into the consumer utility function [36]. Here, $lnquality_{cit}$ represents the estimated product quality, where $\ln\left(q_{fhit}\right) + \sigma ln\left(p_{fhit}\right) = \alpha_h + \alpha_{it} + \varepsilon_{fhit}$, with q_{fhit} denoting the quantity and p_{fhit} the price of products exported by the enterprise to importing countries in year t. The elasticity of substitution, σ, is based on import demand elasticity data computed by Broda and Weinstein (2006) aggregated at the HS two-digit product level [37].

To ensure the additivity of product quality, it undergoes standardization. Based on this standardized measure $Q_{fhit}^{std} = [Q_{fhit} - \min(Q_{fhit})]/[\max(Q_{fhit}) - \min(Q_{fhit})]$, product quality is weighted by the ratio of the export value of products to the total export value of the enterprise, yielding the weighted average quality of exported products $quality_{ft} = \sum_{h\in\Omega} (value_{fhit}/\sum_i value_{fhit}) \times Q_{fhit}^{std}$. Here, Ω denotes the collection of enterprise-exported products, and $value_{fhit}$ represents the export value of products to importing countries in year t. To mitigate the potential impact of outliers, the natural logarithm of the quality of exported products by enterprises is employed as the dependent variable in this study.

4.2.2. The Core Explanatory Variable

Smart city construction did_{ct} refers to the interaction between the experimental group's dummy variable $treat_c$ and the dummy variable for the experimental period $post_t$. Due to the fact that the enterprise sample used in this study is matched with the China Customs Trade Database and the China Industrial Enterprise Database, with the most recent data available up to 2015, and considering that the three rounds of national smart city pilot projects initiated by the Chinese government took place in 2012, 2013, and 2014, the focus of this study is on the short-term effects of smart city initiatives on the quality of export products by enterprises during the sample period. Firstly, this study uses the 2012 first

batch of national smart city pilot projects as a quasi-natural experiment. A single-time DID (difference-in-differences) approach is constructed for econometric regression, serving as the main empirical method. Secondly, utilizing the three batches of national smart city pilot projects in 2012, 2013, and 2014 as a quasi-natural experiment, a multi-point DID regression is constructed as supplementary empirical evidence to enhance the robustness of the empirical analysis. In terms of variable construction, experimental group dummy variables $treat_c$ are set based on whether they are affected by national smart city pilot policies, where cities designated as national smart city pilot projects are assigned a value of one for the experimental group, and cities not designated as such are assigned a value of zero for the control group. Experimental period dummy variables $post_t$ are set based on the timing of national smart city pilot projects; years starting from the year of designation and thereafter are assigned a value of one, whereas all years before the designation are assigned a value of zero. This construction yields the interaction did_{ct} between the experimental group's dummy variable $treat_c$ and the experimental period's dummy variable $post_t$, which represents the net impact of national smart city pilot projects on the quality of enterprise export products.

4.2.3. Control Variables

Control variables *Control*. Drawing on existing research, this study selects control variables including enterprise characteristics, industry characteristics, and city characteristics. Regarding enterprise characteristics, capital intensity $lnkl$ is quantified by taking the logarithm of the ratio between the annual average net value of fixed assets and the total number of employees; enterprise age, denoted as $lnage$, is determined by taking the logarithm of the difference between the observation year and the year of establishment, with one added to this difference; employment size $lnstaff$ is represented by the logarithm of the number of employees at the enterprise; and asset size lnk is characterized by the logarithm of total fixed assets. In terms of industry characteristics, market competitiveness $lnhhi$ is quantified using the Herfindahl index $hhi = \sum_{i \in j} (sale_{it}/sale_{jt})^2$, where smaller values indicate lower market concentration and thus higher market competitiveness, $sale_{it}$ and $sale_{jt}$ representing the sales of the enterprise and industry in year t, respectively. Concerning city characteristics, economic development level $lngdp$ is represented by the logarithm of per capita real GDP, adjusted by the real GDP using the price index with 2003 as the base year; openness to foreign cooperation $lnfdi$ is measured by the logarithm of the ratio of foreign direct investment to GDP; and population density $lnpop$ is described by the logarithm of the year-end total population divided by the built-up area.

4.3. Data Processing and Matching

The data utilized in this study are primarily sourced from the China Customs Trade Database, the China Industrial Enterprise Database, and the China City Statistical Yearbook, with the analysis covering the period from 2007 to 2015. Key considerations for selecting the sample period: Firstly, it is necessary to use data from the China Customs Trade Database to measure the quality of enterprise export products. However, since 2016, some key variables in this database have been missing. Therefore, this study limits the data sample to the most recent year up to 2015. Similar studies, such as those by Hong et al. (2022) [18], Destefano and Timmis (2024) [21], and Xu and Tian (2023) [23], also use data from 2015 and earlier years. Secondly, the data used to calculate the artificial intelligence development indicators primarily come from the IFR Industrial Robots Database, the China Industrial Enterprises Database, and the China Urban Statistical Yearbook. Notably, the IFR Industrial Robots Database only provides comprehensive data on industrial robots in China's sub-industries from 2007 onwards, so this study sets the starting year of the sample at 2007. Additionally, the most recent data available in the China Industrial Enterprises Database, which is used for calculating the artificial intelligence development indicators, are also up to 2015. In fact, since the concept of artificial intelligence was introduced, the field has experienced three major waves of development. The first wave, spanning approximately from 1950 to 1979,

focused on simulating expert decision-making through symbolic reasoning and logical computation. The second wave, from around 1980 to 2006, was distinguished by advancements in complex model simulations and the ability to replicate human thinking and behavior. The third wave, beginning around 2007, marks a period of rapid expansion, characterized by capabilities such as cross-disciplinary integration, human–machine collaboration, and autonomous control. Thus, this study has chosen the sample period from 2007 to 2015. The starting year closely aligns with the onset of the third wave of artificial intelligence development, providing a robust reflection of its rapid progress. By 2015, this nine-year period since the beginning of the third wave offers a well-representative timeframe for examining the development of artificial intelligence.

To meet research requirements, the data underwent several processing steps: Firstly, samples failing to meet the specified criteria were removed from the China Customs Trade Database. Secondly, samples that did not meet the criteria from the China Industrial Enterprise Database were excluded. Thirdly, following Yu (2015) [38] methodology, we first matched the cleaned samples from the China Customs Trade Database and the China Industrial Enterprise Database by year and enterprise name. Subsequently, the remaining samples were matched using criteria such as year, company postal code, and the last seven digits of the telephone number, with the final dataset, including only those samples that were successfully matched in both phases. Fourthly, with the samples successfully matched between the China Customs Trade Database and China Industrial Enterprise Database, matching was conducted against the China City Statistical Yearbook data based on year and city name to compile Dataset A. Fifthly, Dataset A was refined for the single-period DID regression by removing samples from Beijing, Tianjin, Shanghai, and Chongqing, as well as those from prefecture-level cities and districts not fully covered in the smart city pilot projects of 2012, 2013, and 2014. Additionally, newly added pilot cities in 2013 and 2014 were excluded, resulting in the sample being denoted as Empirical Dataset AA. For multiple-point DID regression, Dataset A was cleaned similarly, resulting in Empirical Dataset AB. Statistical characteristics of variables in Empirical Dataset AA are presented in Table 1.

Table 1. Statistical Characteristics of Variables.

Variable	N	Mean	SD	Max	Min
lnquality	155,104	0.4330	0.0781	0.6931	0.0000
did	155,104	0.1813	0.3853	1.0000	0.0000
lnkl	155,104	5.3793	1.1131	8.5621	2.9161
lnage	155,104	2.2187	0.6334	4.7958	0.0000
lnstaff	155,104	5.4634	1.0782	11.9722	2.0794
lnk	155,104	9.4297	1.6742	13.8414	5.3982
lnhhi	155,104	0.0087	0.0164	0.6931	0.0004
lngdp	155,104	15.6329	0.6357	16.7597	12.6418
lnfdi	155,104	0.0303	0.0219	0.1092	0.0000
lnpop	155,104	10.5227	0.6292	12.7100	6.9438

5. Empirical Results

5.1. Basic Results

The effect of smart city construction on the quality of enterprise export products is analyzed through baseline regression results, which are detailed in Table 2.

Columns (1)–(3) present the results of single-point DID regressions, while columns (4)–(6) present results from multiple-point DID regressions. Columns (1) and (4) in the analysis control solely for city and year-fixed effects without accounting for additional variables. The core explanatory variables show statistically significant positive coefficients at the 1% level, suggesting that smart city construction enhances the quality of enterprise export products. To mitigate omitted variable bias, columns (2) and (5) introduce control variables, with results similarly showing significant positive coefficients for the core explanatory variables at the 1% level. Furthermore, columns (3) and (6) adjust for more granular enterprise fixed

effects that do not vary over time, again indicating significantly positive coefficients for the core explanatory variables. The combined results from single-point and multiple-point DID regressions demonstrate a robust and significant policy-driven effect of smart city construction on improving enterprise export product quality.

Table 2. Presents the Baseline Regression Results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Single Time-Point DID			Multiple Time-Point DID		
did_one	0.0047 ***	0.0045 ***	0.0052 ***			
	(0.0009)	(0.0009)	(0.0007)			
did_multi				0.0042 ***	0.0041 ***	0.0040 ***
				(0.0007)	(0.0007)	(0.0005)
Constant	0.4322 ***	0.5280 **	0.5467 ***	0.4316 ***	0.2339	0.5032 ***
	(0.0004)	(0.2059)	(0.0611)	(0.0004)	(0.1782)	(0.0528)
Control variables	No	Yes	Yes	No	Yes	Yes
City fixed effect	Yes	Yes	No	Yes	Yes	No
Enterprise fixed effect	No	No	Yes	No	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155,104	155,104	145,601	195,183	195,183	183,185
R^2	0.0342	0.0419	0.8282	0.0379	0.0460	0.8270

Note: Standard errors in parentheses are clustered at the enterprise level. *** and ** denote significance at the 1% and 5% levels, respectively.

5.2. Parallel Trend Test

In the context of the baseline regression, the analysis determines the causal relationship between smart city construction and the quality of enterprise export products. However, the effectiveness of the Difference in Differences (DID) model is built upon the parallel trends assumption, which states that prior to the implementation of the smart city pilot policy, the changes in the quality of enterprise export products in both the treatment and control groups should follow a roughly parallel time trend. The specific estimation is set as follows:

$$\ln quality_{cit} = \gamma_0 + \sum_{k=-5}^{4} \delta_t D_{ct}^k + \sum \gamma_j Control + \mu_i + \nu_t + \varepsilon_{cit} \quad (10)$$

Here, D_{ct}^k represents a series of dummy variables for the smart city pilot policy. Assuming the policy year when a city obtains approval for the smart city pilot is $post_t$, let k denote the difference from the current year. The symbols for other variables have the same meanings as in Equation (9). δ_t is the key parameter in this section, representing the differential effect of the smart city pilot policy on the change in export product quality between the experimental and control groups over time k. During periods when the relative time of smart city pilot policy implementation δ_t is less than zero, if the trend of δ_t changes smoothly and insignificantly, it indicates compliance with the parallel trends assumption. Conversely, if δ_t exhibits a marked upward or downward trend, it suggests that there were systematic differences between the treatment and control groups prior to the smart city pilot's implementation, which violates the parallel trends assumption. The test outcomes are illustrated in Figure 2. From the figure, it can be observed that during periods when the smart city pilot policy implementation relative time δ_t is less than zero, the regression coefficient changes smoothly and insignificantly. This finding shows that, prior to the smart city pilot policy, the quality of enterprise export products did not significantly differ between the experimental and control groups, thereby adhering to the parallel trends assumption. During periods when the smart city pilot policy implementation relative time δ_t is greater than or equal to zero, the regression coefficient shows a significant and substantial increase. At a relative time of k = 2 for the smart city pilot, the peak value is observed, suggesting

that the pilot policy substantially improves export product quality and creates a significant disparity between the experimental and control groups.

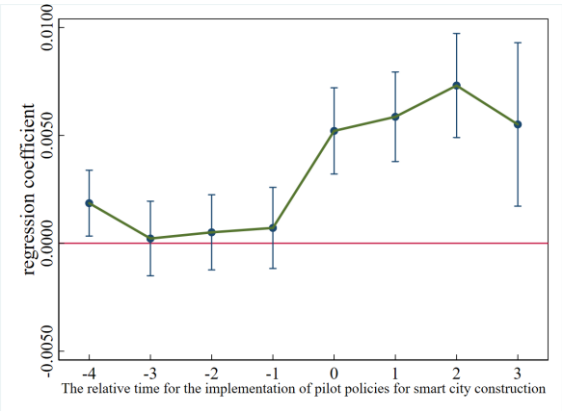


Figure 2. Parallel trend test.

5.3. Placebo Test

Another concern in identifying the DID model assumptions is the impact of omitted variables and random factors on the estimation results. Following the approaches outlined by La Ferrara et al. (2012) and Cai et al. (2016), a placebo test is performed by altering the list of experimental cities involved in smart city projects [39,40]. An equivalent number of placebo pilot cities are randomly selected from the sample cities, matching the number of pilot cities in the 2012 batch of national smart city projects, while the remaining cities serve as placebo control cities. This creates a false variable substitution as described earlier, theoretically generated randomly. Following Equation (9), the regression coefficients are re-estimated. A significant non-zero regression coefficient indicates an error in this study's regression results, suggesting that omitted variables or random factors have influenced the regression results. This process is repeated 500 times, resulting in 500 regression coefficients and their corresponding *p*-values. Figure 3 illustrates the kernel density distribution for these 500 coefficients along with their associated *p*-values. From the probability of these spurious regression coefficients, we can determine if factors aside from smart city pilot policies have a significant effect on the quality of enterprise export products. It is apparent from the graph that the regression coefficients cluster around zero, resembling a normal distribution, indicating that most of the regression findings are not statistically significant. Additionally, the regression coefficients obtained from the false experiments are mostly distributed to the left of the vertical dashed line, indicating a low-probability event in this placebo test. This aligns with the expected outcomes of the placebo test, suggesting that there are no significant omitted variable issues in the model setup. Furthermore, any impact of unobservable factors on the regression results can be ruled out, thus ensuring the robustness of the research conclusions.

5.4. Other Robustness Checks

To further validate the study's conclusions, additional robustness checks are carried out (Table 3). Firstly, PSM-DID testing is performed. This study selects a set of control variables (economic development level, openness to foreign cooperation, population density) and urban capital scale (calculated using fixed asset investment based on perpetual inventory method), infrastructure (measured by per capita road area), and human capital (proportion of university students to total population) as matching criteria. Nearest neighbor matching is employed to filter samples, and the regression results for the matched samples are presented in the first column. Secondly, to exclude the effects of policy disturbances, time dummy variables representing similar smart city pilot project impacts are added to assess their influence on the research findings. The results of these regressions are presented in column (2). Thirdly, the dependent variable is substituted. Following Fan et al.

(2015), and using a product substitution elasticity of five, the study recalculates the quality of enterprise export products, with the results displayed in column (3) [41]. Additionally, the average price of products exported to other countries is used as an instrumental variable for the export price to importing countries. This approach allows for a reassessment of the quality of exported products, with the results presented in column (4). Fourthly, to reduce the impact of outlier samples on the regression results, bilateral trimming is performed on corporate export product quality at the 2.5% level, with the resulting regression findings shown in column (5). Fifthly, we conduct an instrumental variable test using provincial fiber optic density, the number of post offices per million people, and fixed telephones per million people. These variables serve as instruments for the core explanatory variables, representing a more extensive urban infrastructure, and they are likely to correlate with the selection of national smart city pilot areas. Meanwhile, it is less probable for microeconomic export product quality to influence these macro-level instrument variables. The correlation and exogeneity requirements of instrumental variables are satisfied, and the results of two-stage least squares estimation (2SLS) regression are presented in the sixth column. Consistent results from the tests reveal a significant beneficial effect of smart city construction on enhancing the quality of enterprise export products. This supports the validity of theoretical Hypothesis 1.

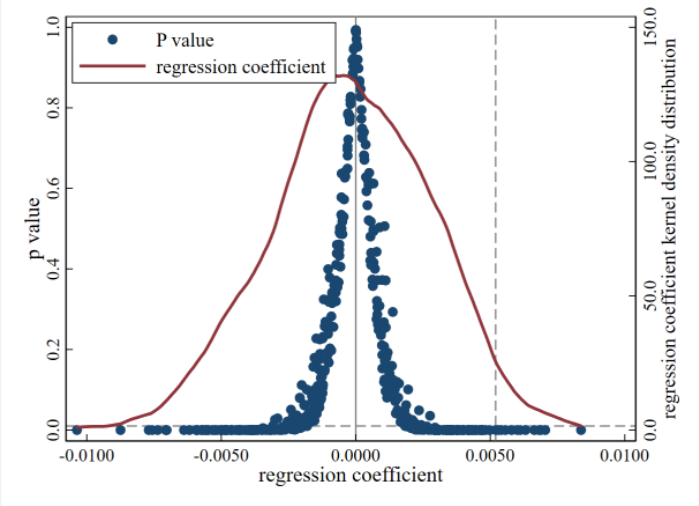


Figure 3. Placebo Test.

Table 3. Other Robustness Tests Results.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Single Time-Point DID						
did_one	0.0052 *** (0.0007)	0.0046 *** (0.0007)	0.0042 *** (0.0005)	0.0054 *** (0.0008)	0.0049 *** (0.0006)	0.0184 ** (0.0089)
Identifiability Test						298.752 <0.00>
Weak Instrument Test						87.249 [13.91]
Observations	140,756	145,601	145,601	113,634	145,601	145,601
Panel B: Multiple Time-Point DID						
did_multi	0.0049 *** (0.0006)	0.0041 *** (0.0006)	0.0038 *** (0.0004)	0.0045 *** (0.0007)	0.0046 *** (0.0006)	0.0266 *** (0.0072)
Identifiability Test						481.419 <0.00>

Table 3. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
Weak Instrument Test						147.980 [13.91]
Observations	178,909	183,185	183,185	141,715	183,185	183,185
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses are clustered at the enterprise level. *** and ** denote significance at the 1% and 5% levels, respectively. Kleibergen–Paap rk LM statistic is used for the over-identification test, where < > denotes the corresponding *p*-value of the statistic; Kleibergen–Paap rk Wald F statistic is used for the weak IV test, where [ ] contains the critical values of the Stock–Yogo weak ID test at the 10% significance level.

6. Heterogeneity Analysis

6.1. Regional Heterogeneity Testing

The data are divided into three regional sub-samples: Eastern, Central, and Western, with the results shown in Table 4. Results from single-point and multi-point DID regressions reveal that the statistical significance of the core explanatory variable's coefficient is observed exclusively in the Eastern region. This indicates that, compared to the Central and Western regions, the impact of smart city construction on enhancing the quality of enterprise export products is notably stronger in the Eastern region. This may be due to the fact that, compared to the Central and Western regions, the Eastern region has greater advantages in talent development, industrial clustering, and technological innovation. As a leading area for artificial intelligence development in China, the Eastern region's promotion of smart city construction is expected to drive urban network infrastructure development, enhance informatization of government and public services, and accelerate applications like smart logistics, smart payments, and smart finance. For the Eastern region, where the application rate of artificial intelligence in enterprises is relatively high, smart city pilot projects are likely to have a more pronounced positive impact on the improvement of corporate export product quality.

Table 4. Heterogeneity test results of the three major regions in China.

	(1)	(2)	(3)	(4)	(5)	(6)
	The Eastern Region		**The Central Region**		**The Western Region**	
	Single Time-Point DID	**Multiple Time-Point DID**	**Single Time-Point DID**	**Multiple Time-Point DID**	**Single Time-Point DID**	**Multiple Time-Point DID**
did_one	0.0053 *** (0.0007)		0.0034 (0.0024)		−0.0102 (0.0101)	
did_multi		0.0045 *** (0.0006)		0.0006 (0.0016)		0.0006 (0.0031)
Constant	0.5575 *** (0.1070)	0.4568 *** (0.0967)	0.4167 *** (0.0817)	0.4177 *** (0.0790)	1.5138 ** (0.7048)	0.6572 *** (0.2066)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,674	155,629	13,020	18,696	3822	8730
R^2	0.8313	0.8315	0.8185	0.8174	0.7925	0.7939

Note: Standard errors in parentheses are clustered at the enterprise level. *** and ** denote significance at the 1% and 5% levels, respectively.

6.2. Industry Heterogeneity Testing

The entire sample is divided into two groups: labor-intensive industries and capital-technology-intensive industries, as shown in Table 5.

Table 5. Heterogeneity test results for industries with different factor intensities.

	(1)	(2)	(3)	(4)
	Labor-Intensive Industries		Capital-Technology-Intensive Industries	
	Single Time-Point DID	Multiple Time-Point DID	Single Time-Point DID	Multiple Time-Point DID
did_one	0.0034 *** (0.0011)		0.0065 *** (0.0007)	
did_multi		0.0035 *** (0.0008)		0.0047 *** (0.0006)
Constant	0.7101 *** (0.1734)	0.5142 *** (0.1430)	0.6540 *** (0.0741)	0.4827 *** (0.0626)
Control variables	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Observations	60,982	77,223	83,616	104,593
R^2	0.8057	0.8012	0.8234	0.8231

Note: Standard errors in parentheses are clustered at the enterprise level. *** denote significance at the 1% levels.

Results from both single-point and multiple-point DID regressions reveal a significantly positive coefficient for the core explanatory variable in both labor-intensive and capital-technology-intensive industries. This suggests that smart city construction has promoted the quality of enterprise export products in both sectors, with a notably greater effect in capital-technology-intensive industries. This disparity may stem from the government-led nature of smart city construction, which frequently involves targeted support for key local industries, including high-end equipment, intelligent manufacturing, smart logistics, smart finance, and smart transportation. As a result, the advantages of smart city construction are more fully realized in capital-technology-intensive industries.

6.3. Heterogeneity Testing of Enterprises

Using the registration type of enterprises as a criterion, the entire sample is categorized into three groups: foreign-funded, private, and state-owned enterprises. The results are presented in Table 6.

Regression results from both single-point DID and multi-point DID indicate that the regression coefficients for the core explanatory variables are positively significant at the 1% level in foreign-funded and private enterprises. In contrast, for state-owned enterprises, only the single-point DID results are significant at the 10% level, while the multi-point DID results lack significance. This indicates that, compared to state-owned enterprises, smart city construction more effectively enhances the quality of exported products in foreign-funded and private enterprises. It may be because, despite state-owned enterprises having a relatively strong market position, resource advantages, and monopolistic status in certain industries, they are also burdened with social responsibilities such as infrastructure development, public service provision, job creation, improving resident welfare, and environmental protection. Confronted with the artificial intelligence technology revolution, state-owned enterprises may implement cautious policies for artificial intelligence adoption, which can delay the policy-driven improvements in product quality through smart city construction. In contrast, non-state-owned enterprises, driven by strong motives to enhance market competitiveness and capture market share through the digital transformation of

enterprises using new technologies like artificial intelligence, demonstrate a more pronounced impact of smart city construction, especially for foreign-funded enterprises. Smart city construction expands the urban FDI frontier, facilitating foreign-funded enterprises to leverage their technological advantages from their home countries to introduce more high-precision intelligent machine tools, industrial robots, and other advanced artificial intelligence equipment. Therefore, smart city construction exhibits the greatest impact on foreign-funded enterprises.

Table 6. Heterogeneity test results for different ownership systems of enterprises.

	(1)	(2)	(3)	(4)	(5)	(6)
	Foreign Enterprise		**Private Enterprise**		**State-Owned Enterprise**	
	Single Time-Point DID	**Multiple Time-Point DID**	**Single Time-Point DID**	**Multiple Time-Point DID**	**Single Time-Point DID**	**Multiple Time-Point DID**
did_one	0.0055 *** (0.0010)		0.0051 *** (0.0009)		0.0099 * (0.0055)	
did_multi		0.0049 *** (0.0008)		0.0036 *** (0.0007)		0.0022 (0.0040)
Constant	0.5444 *** (0.1229)	0.4767 *** (0.1068)	0.5871 *** (0.0803)	0.5139 *** (0.0678)	0.4460 ** (0.1735)	0.5889 *** (0.1705)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,387	77,284	79,727	100,998	3487	4903
R^2	0.8200	0.8185	0.8347	0.8332	0.7931	0.7955

Note: Standard errors in parentheses are clustered at the enterprise level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

7. Mechanism Testing and Expansion Analysis

7.1. Mechanism Testing: The Impact Path of Artificial Intelligence Development

Based on the earlier analysis, this study finds that smart city construction significantly enhances the quality of enterprise export products. Here, the focus is on examining whether the promotion of artificial intelligence development serves as an indirect mechanism through which smart city construction enhances the quality of enterprise export products. Since artificial intelligence is still in its nascent stage and is deeply integrated across various industries, there is currently a lack of comprehensive and authoritative official statistics. Additionally, the academic community also lacks universally recognized accounting metrics for artificial intelligence development. To meet empirical research needs and use available data, this study develops a comprehensive index for measuring artificial intelligence development at the prefecture level and above in Chinese cities.

This index encompasses three dimensions: artificial intelligence infrastructure development, artificial intelligence product services, and artificial intelligence production applications. Specifically, within the dimensions of artificial intelligence infrastructure development and product services, the infrastructure development is represented by two sub-indicators: the number of Internet broadband users per hundred people and the number of mobile phone users per hundred people in cities. Artificial intelligence product services are represented by two sub-indicators: per capita telecommunications services and the share of employment in computer services and software industries. In the dimension of artificial intelligence production applications, following Acemoglu and Restrepo (2020) [24], three sub-indicators are used: the proportion of smart manufacturing enterprises in cities, the proportion of revenue from smart manufacturing enterprises in cities, and the penetration rate of industrial robots in cities. Data primarily derive from the Chinese Industrial

Enterprise Database, China City Statistical Yearbook, and the International Federation of Robotics (IFR) Industrial Robotics Database.

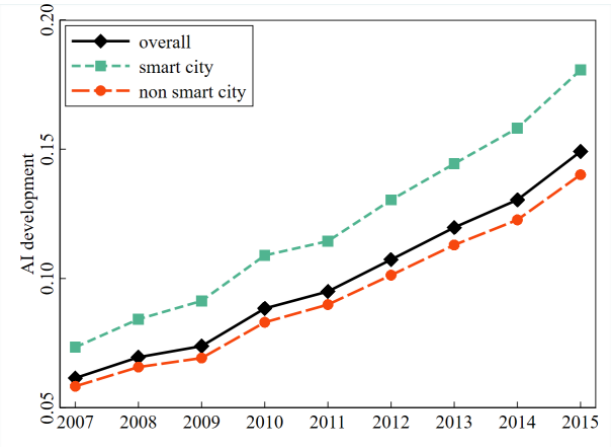
It is worth noting the following: Based on data availability and the presence of missing data, this study initially selects 284 prefecture-level and above cities as samples for measurement. Regarding the calculation formula for the penetration rate of industrial robots in cities, it is given by: $Rob_{ct} = \sum_j (L_{cjt_0} / \sum_j L_{cjt_0}) \times (Rob_{jt} / L_{jt_0})$, where c represents the city, j represents the industry, and t represents the year. The penetration rate of industrial robots in city c in year t, denoted as Rob_{ct}, indicates the impact of industrial robot applications on the city, with higher values suggesting a greater impact. L_{cjt_0} represents the number of workers in industry j in city c in year t; L_{jt_0} represents the number of workers in industry j nationwide in year t; Rob_{jt} represents the number of industrial robots used in industry j nationwide in year t. As the IFR has only provided detailed records of China's industrial robot data by sector from 2006 onwards, this study sets the base year as 2006, with the period of analysis from 2007 to 2015.

This study employs the entropy weight method to objectively assign weights and conduct dimensionality reduction for the sub-indicators, thereby calculating a comprehensive index of artificial intelligence development in cities. Firstly, sub-indicators are standardized as follows: $Z_{\mathrm{it}} = [X_{\mathrm{it}} - \min(X_i)] / [\max(X_i) - \min(X_i)]$, where X_{it} represents the baseline value of sub-indicator i in year t, $\max(X_i)$ and $\min(X_i)$ represent the upper and lower bounds of the sub-indicator i in year t, and $Y_{it} = Z_{it} / \sum_{t=1}^{m} Z_{it}$ represents the standardized value of sub-indicator i in year t. Next, the entropy of sub-indicators is calculated: $E_i = (-1/\ln m) \times \sum_{t=1}^{m} Y_{it} \times \ln Y_{it}$, where m represents the number of years in the sample period. Subsequently, the redundancy of information entropy d_i and the weights of the sub-indicators i are calculated: $W_i = (1 - E_i) / \sum_{t=1}^{m} (1 - E_i) = d_i / \sum_{t=1}^{m} d_i$. Finally, a weighted sum is used to obtain the comprehensive index of artificial intelligence development for each city: $AI_{ct} = \sum_{i=1}^{n} Z_{it} \times W_i$. The calculated results are then matched with the dataset mentioned earlier based on year and city name.

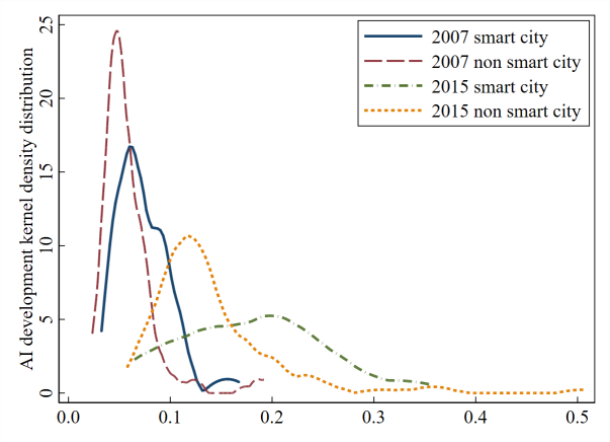
Figure 4 presents the calculated results of artificial intelligence development in Chinese cities from 2007 to 2015. Figure 4a shows a significant upward trend in the overall level of artificial intelligence development. However, the effect of artificial intelligence development in smart cities is more pronounced, with the gap between smart cities and non-smart cities widening over time. Figure 4b also illustrates that the distribution curve of artificial intelligence development shifts markedly to the right as time progresses, indicating that the artificial intelligence development in Chinese cities is dynamically evolving from a low level to a high level. Compared to non-smart cities, the distribution curve for smart cities shifts further to the right, indicating a stronger growth rate in artificial intelligence development within smart cities.

To verify Hypothesis 2 and identify how smart city construction indirectly affects the quality of enterprise export products, this study first examines its impact on artificial intelligence development (see Table 7). It then analyzes how artificial intelligence development influences the quality of enterprise export products, with results shown in Table 8. As previously mentioned, existing studies often use the penetration rate of industrial robots as a proxy variable for artificial intelligence development. For robustness, we report the results using both artificial intelligence development $lnAI$ and the penetration rate of industrial robots $lnRob$ as different proxy variables.

Based on the regression results from Table 7 on the impact of smart city construction on artificial intelligence development, controlling for variables, varying regression models (single-point DID and multi-point DID), and employing alternative measures for artificial intelligence development, the regression coefficients of the core explanatory variables are consistently significant at least at the 5% level. This robustness across different specifications indicates that smart city construction indeed promotes artificial intelligence development, generating significant exogenous impacts on local artificial intelligence development.



(**a**) Time Series of Artificial Intelligence Development



(**b**) Kernel Density Plot of Artificial Intelligence Development

Figure 4. Artificial Intelligence Development Estimates for Chinese Cities (2007–2015). Note: "Smart cities" refer to the sample regions designated as national smart city pilot areas in China; other prefecture-level cities and above are categorized as non-smart cities.

Analyzing the regression results from Table 8 on the impact of artificial intelligence development on the quality of enterprise export products reveals that whether using a composite index of artificial intelligence development (columns 1–3) or city-level industrial robot penetration indicators (columns 4–6), the regression coefficients of the core explanatory variables are significantly positive at the 1% level. This suggests that higher levels of urban artificial intelligence development are advantageous for enhancing the quality of enterprise export products.

Integrating the regression outcomes from Tables 7 and 8, smart city construction serves as a robust quasi-natural experiment to foster artificial intelligence development. Leveraging this as a policy lever can significantly enhance urban artificial intelligence development, thereby driving improvements in the quality of enterprise export products. Thus, promoting artificial intelligence development through smart city construction represents a significant policy transmission mechanism that validates theoretical Hypothesis 2.

Table 7. Mechanism Test Results (I): Impact of Smart City Construction on Artificial Intelligence Development.

	(1)	(2)	(3)	(4)
	Single Time-Point DID		**Multiple Time-Point DID**	
Panel A: Testing Based on the lnAI Indicator				
did	0.0107 ** (0.0047)	0.0105 ** (0.0046)	0.0062 ** (0.0030)	0.0060 ** (0.0029)
Constant	0.0923 *** (0.0004)	0.0725 (0.3652)	0.0908 *** (0.0004)	−0.4942 (0.3470)
Observations	1327	1327	1854	1854
R^2	0.8735	0.8738	0.8724	0.8730
Panel B: Testing Based on the lnRob				
did	0.1470 ** (0.0676)	0.1395 ** (0.0658)	0.0765 *** (0.0211)	0.0745 *** (0.0209)

Table 7. *Cont.*

	(1)	(2)	(3)	(4)
	Single Time-Point DID		**Multiple Time-Point DID**	
Constant	1.5973 *** (0.0064)	−1.0549 (5.6178)	1.5997 *** (0.0063)	−5.0622 (3.3824)
Observations	1327	1327	1854	1854
R^2	0.9556	0.9564	0.9533	0.9538
Control variables	No	Yes	No	Yes
City fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses are clustered at the enterprise level. *** and ** denote significance at the 1% and 5% levels, respectively.

Table 8. Mechanism Test Results (II): Impact of Artificial Intelligence Development on the Quality of Enterprise Export Product.

	(1)	(2)	(3)	(4)	(5)	(6)
lnAI	0.0703 *** (0.0138)	0.0599 *** (0.0139)	0.0368 *** (0.0106)			
lnRob				0.0069 *** (0.0013)	0.0066 *** (0.0013)	0.0065 *** (0.0011)
Constant	0.4240 *** (0.0017)	0.1807 (0.1786)	0.5132 *** (0.0530)	0.4198 *** (0.0024)	0.1694 (0.1784)	0.5250 *** (0.0531)
Control variables	Yes	Yes	No	Yes	Yes	No
City fixed effect	No	No	Yes	No	No	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	No	Yes	Yes	No
Observations	195,183	195,183	183,185	195,183	195,183	183,185
R^2	0.0378	0.0459	0.8269	0.0379	0.0460	0.8270

Note: Standard errors in parentheses are clustered at the enterprise level. *** denote significance at the 1% levels.

7.2. Extended Analysis: Effects of Factor Marketization

Given that factor market distortions are a significant practical constraint on improving the quality of enterprise export products, these distortions impede the free flow of production factors, distort price signals, and foster rent-seeking behavior among firms, resulting in suboptimal resource allocation and inefficiencies in capital and labor usage. This leads to suboptimal allocation of resources, resulting in inefficient use of capital and labor. The more severe the distortions, the more likely skilled labor is to be allocated to non-productive sectors, leading to talent misallocation and increased rent-seeking behavior by entrepreneurs rather than innovation. Additionally, factor market distortions undermine the competitive mechanism of market selection, allowing inefficient firms to access cheap production factors and preventing their exit from the market, which hampers the improvement of export product quality. Based on the theoretical analysis presented, one mechanism through which smart city construction can enhance the quality of enterprise export products is by driving the aggregation of data through intelligent sensors embedded in buildings, power grids, and transportation infrastructure. By integrating these data with modern information technologies such as big data, cloud computing, and supercomputing, smart city construction facilitates the efficient and dynamic allocation of urban resources. Given this context, can smart city construction promote the improvement of product quality for export by enhancing the efficiency of factor market allocation channels? Building upon

Equation (9), this paper introduces an interaction term between smart city construction and factor marketization to identify the effect of smart city construction on the quality of exported products through the efficiency of factor market allocation, extending the findings from earlier research.

Theoretically, smart city construction can improve factor market allocation efficiency, thereby significantly enhancing the policy impacts on the quality of enterprise export products. Specifically, in terms of the urban business environment, smart city construction enhances smart governance in administrative services by reducing information barriers between the government and the public, increasing transparency, and mitigating corrupt practices such as secretive dealings and nepotism. This reduces opportunities and space for rent-seeking behaviors, contributing to a fairer and more equitable competitive environment. From the standpoint of enterprise production and operation, smart city construction promotes deep integration of artificial intelligence and digital economy with traditional factors, enhancing the inclusiveness and coordination of factor markets. It facilitates rational guidance for the effective allocation of factors, achieving optimal efficiency in the process of "aggregation–optimization–re-aggregation" of production factors. Enterprises can utilize advanced information technologies to promptly grasp market supply and demand conditions, swiftly adjust organizational and operational models, mitigate resource misallocation issues, and improve the efficiency of capital, labor, and other production factors. This paper then investigates whether smart city construction improves factor marketization and thereby enhances the quality of enterprise export products. Factor marketization is measured in two ways: Firstly, using a composite index of factor market development, which integrates information from three dimensions—labor market development, capital market development, and technology market development; higher values indicate greater levels of factor marketization. Secondly, indicators representing distortions in labor and capital factor markets are computed in this study using data from the China Statistical Yearbook and China City Statistical Yearbook. Given the dual-sided nature (reverse and direct) of these distortions, the reciprocal of the reverse distortion side is used to obtain positive indicators of labor and capital factor marketization. Regression results are presented in Table 9.

The findings of the examination of the factor marketization effects of smart city construction on the quality of enterprise export products are reported in Table 9. The single-point DID regression results, shown in columns (1) to (3), reveal that the interaction terms between the core explanatory variables and factor market development, labor marketization, and capital marketization show significant positive coefficients at least at the 5% level. This implies that smart city construction can improve the quality of enterprise export products by enhancing factor market optimization. The results from multi-point DID analysis in columns (4)–(6) similarly show significantly positive coefficients for the interaction terms, further co-enterprising that smart city pilot projects can positively impact the enhancement of product quality through strengthening factor marketization channels. This may be attributed to smart city construction facilitating a reduction in government rent-seeking opportunities, fostering transparent government services, and creating a fair competitive business environment, thereby establishing robust mechanisms for factor marketization. Additionally, smart city initiatives promote the integration of artificial intelligence and digital economy with traditional factors, enabling businesses to enhance efficiency in monitoring market demands, swiftly transforming organizational production and operational models, and thus improving how labor and capital are allocated, which in turn enhances the quality of enterprise export products.

Table 9. Extended Analysis: Testing the Effects of Factor Marketization on Quality Improvement of Exported Products.

	(1)	(2)	(3)	(4)	(5)	(6)
	Single Time-Point DID			**Multiple Time-Point DID**		
did × lnfy	0.0084 ** (0.0041)			0.0127 *** (0.0028)		
did × lnpl		0.0028 ** (0.0011)			0.0024 ** (0.0011)	
did × lnpk			0.0009 *** (0.0003)			0.0008 *** (0.0003)
Constant	0.5498 *** (0.0611)	0.5560 *** (0.0548)	0.5472 *** (0.0611)	0.5146 *** (0.0526)	0.5051 *** (0.0480)	0.5040 *** (0.0529)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145,601	145,601	145,601	183,185	183,185	183,185
R^2	0.8282	0.8283	0.8282	0.8271	0.8270	0.8270

Note: Standard errors in parentheses are clustered at the enterprise level. *** and ** denote significance at the 1% and 5% levels, respectively.

8. Research Conclusions and Policy Recommendations

8.1. Research Conclusions

Quality improvement plays a significant role in the rise of major economies, and enhancing the quality of enterprise export products is a crucial micro-foundation for supporting high-quality economic development. As the technological revolution in artificial intelligence accelerates, it is crucial to identify policies that can improve export product quality through artificial intelligence development. And smart city construction offers an effective starting point for these policies. This study incorporates artificial intelligence development into the enterprise product quality framework and explores the mechanisms through which smart city construction influences the quality of enterprise export products. To further this analysis, the study uses the smart city construction pilots initiated by the Chinese government as a quasi-natural experiment to promote artificial intelligence development. Utilizing city-enterprise-level data from 2007 to 2015, sourced from the China Customs trade database, the China Industrial Enterprise Database, the Urban Statistical Yearbook, and the IFR Industrial Robot Database, the study applies a difference-in-differences model to investigate the impact and mechanisms of smart city construction on the quality of enterprise export products.

The main conclusions are as follows: (1) Smart city construction significantly drives improvements in the quality of enterprise export products, a conclusion robust across parallel trend tests and placebo tests. This finding provides empirical evidence for establishing the theoretical relationship between smart city construction and the quality of enterprise export products. It enriches the existing literature by offering new perspectives on the economic effects of smart city construction and the factors driving improvements in export product quality. (2) The impact of smart city construction on the quality of enterprise export products varies significantly: significant promotion is observed in eastern regions compared to non-significant effects in central and western regions; greater promotion in capital-intensive industries compared to labor-intensive ones; and significant positive effects on foreign-owned and private enterprises, with stronger effects on foreign-owned enterprises. (3) Mechanism tests and extended analyses reveal that artificial intelligence development in Chinese cities shows an overall increasing trend, with smart cities exhibiting more robust artificial intelligence development, widening the development gap with

non-smart cities. Smart city construction significantly promotes urban artificial intelligence development, thereby driving improvements in the quality of enterprise export products through artificial intelligence development. Furthermore, smart city construction effectively enhances the quality of enterprise export products by strengthening the market-oriented allocation of resources. This not only demonstrates that smart city construction serves as a policy lever to boost the quality of enterprise export products by driving artificial intelligence development, but also reveals the potential connections among smart city construction, artificial intelligence development, and quality of enterprise export products in the literature. It offers new insights for the academic community to establish a theoretical framework linking these three elements and to explore and quantify the driving potential of artificial intelligence development as a transmission mechanism.

8.2. Policy Recommendations

Drawing on the above research findings, this paper offers the following recommendations. Firstly, it is essential to continue advancing smart city construction to establish a solid foundation for improving the quality of enterprise export products. On one hand, the central government should accelerate the formulation of new plans for smart city construction, guiding local cities to leverage new information technologies in creating modern urban "smart governance" ecosystems. On the other hand, local governments should accurately implement smart city construction tasks by developing a unified data-sharing platform that is vertically integrated, horizontally connected, secure, and efficient. This platform should offer real-time dynamic information, risk assessment, early warning, and monitoring capabilities to support business decision-making within the urban smart system. Secondly, it is crucial to apply targeted strategies in smart city construction to improve how smart technologies support the enhancement of the quality of enterprise export products. Smart city construction should be tailored to local conditions and specific enterprise needs. The central government could establish a series of leading smart cities in more developed regions, while offering policy support to less developed areas to create distinctive smart cities with regional influence. And local governments should leverage the advantages of local industries and enterprises by implementing targeted measures, such as technical support and financial assistance, to guide businesses in exploring big data innovations and developing an integrated and enhanced urban management system, or "city brain". This approach aims to continuously channel the city's smart capabilities to ultimately provide diversified and personalized support for improving the quality of exported products. Thirdly, it is important to focus on leveraging smart city empowerment channels to cultivate and strengthen the foundation for new drivers of improving the quality of enterprise export products. Government should leverage smart city construction as a framework to coordinate and advance the development of information infrastructure, including industrial Internet, 5G base stations, domestic and international communications, and data centers. This strategy aims to reduce the costs for enterprises to access artificial intelligence applications. By fostering the growth of intelligent industries, it will encourage businesses to adopt artificial intelligence technologies and enhance the quality of export products. Additionally, governmental efforts should also prioritize accelerating the smart informatization construction in areas such as government and public services. This will establish efficient, convenient, and scientifically precise resource allocation mechanisms, fully realizing the policy benefits of smart city construction.

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