Does Government Digital-Intelligent Construction Improve Total Factor Energy Efficiency? —A Causal Forest Analysis Based on Provincial Panel Data

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Abstract

[Purpose] This study investigates the impact of government digital-intelligent construction on total-factor energy efficiency and its regional heterogeneity, providing empirical evidence for energy policy formulation. [Methods] Using panel data from 30 provincial-level administrative regions in China spanning 2011-2021, we construct an indicator system for government digital-intelligent construction and measure its level via the entropy method. Total-factor energy efficiency is calculated using the super-efficiency SBM model, and the relationship between these variables along with their heterogeneity is empirically analyzed through the causal forest model. [Conclusions] Government digital-intelligent construction exhibits a significant positive effect on total-factor energy efficiency, with an average treatment effect of 0.1841. Regional heterogeneity is pronounced, with the strongest improvement observed in the eastern region and comparatively weaker effects in the central and western regions. Key influencing factors include economic development level, urbanization level, investment in intelligent equipment, and degree of technology application. [Recommendations] Policy design should account for regional characteristics, increase investment in digital-intelligent infrastructure in central and western regions, promote intelligent transformation of traditional industries, and comprehensively enhance energy efficiency.

Full Text

Preamble

Has Government Digital-Intelligent Construction Improved Total Factor Energy Efficiency? —A Causal Forest Analysis Based on Provincial Panel Data

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Abstract: [Objective] This study investigates the impact of government digital-intelligent construction on total factor energy efficiency (TFEE) and its regional heterogeneity, providing empirical evidence for energy policy formulation. [Method] Based on panel data from 30 provincial-level administrative regions in China during 2011-2021, we construct an evaluation index system for government digital-intelligent construction and measure its level using the entropy method; employ a super-efficiency SBM model to calculate TFEE; and utilize a causal forest model to empirically analyze the relationship between the two and its heterogeneity. [Conclusion] Government digital-intelligent construction exhibits a significant positive effect on TFEE, with an average treatment effect of 0.1841. Regional heterogeneity is evident, with the strongest improvement observed in eastern regions and weaker effects in central and western regions. Key influencing factors include economic development level, urbanization level, investment in smart equipment, and degree of technology application. [Recommendation] Policies should emphasize regional characteristics, increase investment in digital-intelligent infrastructure in central and western regions, promote the intelligent transformation of traditional industries, and comprehensively enhance energy efficiency.

Keywords: Government Digital-Intelligence; Total Factor Energy Efficiency; Causal Forest Analysis

Energy constitutes the foundation of the national economy, and improving energy utilization efficiency is directly critical to achieving high-quality economic and social development and the "dual carbon" strategic goals in China. Total factor energy efficiency (TFEE) serves as a crucial benchmark for measuring the advancement and scientific nature of a country' s energy utilization system, representing the core indicator of new-quality productive forces in the energy sector. It comprehensively reflects the coordination efficiency among energy, capital, and labor inputs during production, aligning more closely with the economic connotation of Pareto efficiency [1]. Enhancing TFEE represents the essential path for China to fulfill its "dual carbon" objectives and implement green development principles [2].

With the rapid development of digital technologies such as big data and artificial intelligence, digital-intelligent governance is profoundly transforming the internal and external environments of government administration [3]. Government digital-intelligent construction refers to the comprehensive transformation and upgrading of government governance models, processes, and service methods through digital technologies and intelligent means, achieving efficient, transparent, and intelligent governance [4]. By leveraging big data, artificial intelligence, and the Internet of Things, government digital-intelligent construction enables efficient allocation and precise management of social resources, thereby improving the quality and efficiency of public services [5]. While providing crucial momentum for digital economic development, government digital-intelligent construction also opens new pathways for enhancing energy efficiency.

Since the 18th National Congress of the Communist Party of China, party committees and governments at all levels have accurately perceived the trends of digitalization, efficiency, and green transformation in the energy sector, making a series of major strategic deployments centered on digital government construction and green energy transition.

Li Lianshui et al. employed the non-parametric DEA-Malmquist productivity method to estimate technical efficiency and used panel techniques to evaluate the impact of technological progress on energy efficiency [6]. Huang Qunhui et al. selected historical data as instrumental variables to comprehensively examine, from three dimensions—city, industry, and enterprise—the intensity and internal mechanisms of internet development' s impact on China' s manufacturing efficiency while addressing endogeneity [7]. Zhang Wanli et al. utilized provincial balanced panel data and applied static and dynamic panel models to analyze how intelligence affects energy efficiency, investigating the moderating roles of technological innovation, environmental regulation, and foreign direct investment [8]. Guo Xiaoyang et al. used panel data from 278 prefecture-level cities in China to empirically test the impact of intelligent manufacturing on urban energy utilization efficiency and the role of human-machine collaboration therein [9]. Zeng Liang' en et al., after analyzing the spatiotemporal characteristics of energy carbon emission efficiency, constructed a Tobit regression model and employed mediation effect methods to empirically test how digital inclusive finance improves energy carbon emission efficiency [10]. Feng et al. used panel data covering 186 countries to empirically assess the net effect of digital government on carbon intensity and deeply explore its underlying mechanisms [11]. Li et al. utilized panel data from 258 Chinese cities to study how digital intelligence promotes synergistic improvements in regional pollution and carbon emission reduction, analyzing the influence of market structure and government behavior on this process [12]. Jiang et al. used data from 258 Chinese prefecture-level cities, employed the entropy method to measure energy sustainability, and adopted the difference-in-differences (DID) method to study digital government' s impact on energy sustainability [13].

The classical causal inference methods employed in the aforementioned studies exhibit certain limitations in handling complex non-linear relationships. Due to numerous mediating parameters, the relationship between government digital-intelligence and TFEE is difficult to characterize as linear or simple non-linear; rather, it demonstrates non-parametric features that traditional causal inference methods struggle to capture. Moreover, heterogeneous treatment effects are particularly pronounced in the relationship between government digital-intelligence and TFEE. For instance, the impact of government digital-intelligence on TFEE through mediating factors such as technological innovation, infrastructure, and environmental regulation varies significantly across eastern, central, and western regions, necessitating methodological innovation. Therefore, this paper employs the machine learning-based causal forest method to analyze the impact mechanism of government digital-intelligent construction on TFEE. First, based on existing literature, we theoretically propose relevant hypotheses regarding the potential impacts of government digital-intelligence on TFEE. Second, we construct a scientifically sound evaluation index system for government digital-intelligent construction level and accurately measure it using the entropy method. Third, we adopt a super-efficiency SBM model to calculate TFEE for 30 provincial-level administrative regions in China, comprehensively grasping the current status of regional energy utilization efficiency. Finally, we utilize a causal forest model to empirically analyze the impact of government digital-intelligent construction on TFEE and its heterogeneity. Through this study, we aim to provide valuable references for government energy policy formulation and promote digital-intelligent development in the energy sector.

Research Hypotheses

This paper explores the impact mechanism of government digital-intelligent construction on TFEE and its spatial heterogeneity characteristics. On one hand, government digital-intelligent construction enhances and optimizes TFEE through technological innovation, environmental regulation, and physical infrastructure. On the other hand, it may also reduce TFEE through the energy rebound effect. At the technological innovation level, government digital-intelligent construction can optimize the entire chain efficiency of energy production, distribution, and consumption through data-driven decision-making and intelligent management [8]. Si Linbo et al. argue that the core of improving energy efficiency through digital-intelligent construction lies in data-driven energy management optimization [5]. By leveraging digital technology innovations such as blockchain and IoT to achieve real-time data collection and dynamic adjustment of energy systems [14], energy losses can be effectively reduced. Gong Yipin et al. suggest that big data technology enables governments to monitor energy dynamics in real time and optimize resource allocation [15]; Xiao Zeqing et al. contend that deep embedding of artificial intelligence technology enhances energy utilization precision [16]. Chen Long et al. argue that data-driven methods can help China build a low-carbon sustainable energy operation model [17]. Tang Xueyong et al. propose that future energy systems should be energy-information coupled systems that can further improve energy utilization efficiency through simulation modeling, planning, and operational optimization [18]. At the environmental regulation level, Lin Boqiang et al. find that digital supervision systems (such as emission trading platforms) reduce energy leakage by improving the enforcement efficiency of environmental regulations [19]. At the industrial transformation level, the application of intelligent platforms such as carbon emission monitoring systems compels enterprises to adopt energy-saving technologies [7], achieving green transformation and reducing carbon emissions. Other studies have explored the profound impact of digital-intelligence on energy efficiency across four dimensions—physical foundation, participants, media, and pathways—finding that network infrastructure, communication service development, information technology industry development, and digital technology innovation have varying degrees of positive impact on energy efficiency [20].

However, the impact of technological innovation on energy efficiency is not entirely positive. Li Lianshui et al. find that after technological innovation reduces unit energy consumption costs, enterprises may expand production scale or increase investment in energy-intensive equipment, leading to rising total energy consumption [6]. When environmental regulation intensity is excessively high, it may also inhibit the promoting effect of technological innovation on energy efficiency. Some studies have found that when environmental regulation intensity exceeds 0.0002, its impact on TFEE shifts from positive to negative [21]. Feng Feng et al. discover that the technology spillover effect is significantly higher in central and western regions than in the east, and under the influence of factors such as the energy rebound effect, digital-intelligence in less-developed regions may exacerbate energy-dependent industrial structures [22].

Nevertheless, overall, government digital-intelligent transformation can effectively reduce carbon emissions in administrative processes through intelligent management systems, demonstrating its role as a leader in green governance, while also accelerating green technology innovation and application through policy guidance and financial support [23]. Based on this, we propose Hypothesis 1:

Hypothesis 1: Government digital-intelligent construction has an overall positive effect on TFEE.

China' s provinces and cities with higher energy efficiency are mainly concentrated in the southeastern coastal regions, while those with the lowest efficiency are primarily inland provinces rich in coal resources and dominated by coal consumption [24]. Additionally, spatial agglomeration of energy production capacity exhibits significant regional heterogeneity in its impact on regional energy efficiency. The agglomeration effect promotes energy efficiency in eastern regions but shows an inhibitory effect in central and western regions [25]. Given regional differences in economic development level, industrial structure, and intelligent infrastructure, the impact of government digital-intelligent construction on TFEE may also be heterogeneous. In the economically developed eastern regions, more complete intelligent infrastructure can better leverage the benefits of digital-intelligent construction, whereas central and western regions may see limited effects due to lower economic development levels or heavier dependence on traditional industries. Related research indicates that the improvement of energy utilization efficiency by intelligent manufacturing shows significant regional differences, with central and western regions, due to relatively lagging manufacturing and industrialization processes, able to rapidly achieve production process optimization and significant improvements in energy utilization efficiency through the introduction of intelligent manufacturing technology. Additionally, because contradictions between resource development, economic-social development, and ecological environmental protection persist in resource-based cities, the promotion speed and application depth of intelligent manufacturing technology lag behind non-resource-based cities [9][9]. Zhang Jingxue et al., through their study of carbon emission efficiency in typical underdeveloped areas, find that high-high agglomeration areas of carbon emission efficiency in underdeveloped regions exhibit polarization effects, while low-low agglomeration areas show spillover effects [26].

Accordingly, we propose Hypothesis 2:

Hypothesis 2: The enhancing effect of government digital-intelligent construction on TFEE exhibits regional heterogeneity, which is influenced by economic development level.

Research Design

Model Specification

This paper employs the causal forest model to analyze the impact of government digital-intelligent construction on TFEE. The causal forest model is a machine learning-based causal inference method that combines random forest algorithms with causal model theory, effectively handling heterogeneous treatment effects and overcoming endogeneity issues inherent in traditional regression models [27].

The causal forest model first constructs multiple random trees through a random forest algorithm. The covariate space is randomly partitioned into multiple subspaces, with samples in each subspace divided into treatment and control groups. Within each subspace, the model estimates the Conditional Average Treatment Effect (CATE) by comparing outcome variable differences between treatment and control groups. CATE reflects the average impact of the treatment variable on the outcome variable under specific covariate conditions. By constructing multiple random trees, the causal forest model generates a weighted average of ATE estimates, ultimately producing an overall CATE estimate. Additionally, the model can identify heterogeneous treatment effects under different covariate conditions, thereby revealing differentiated policy tool effects across various conditions [28]. Simultaneously, the model utilizes "sample splitting" technology to ensure confidence interval coverage by overcoming covariate quantity constraints, enhancing the credibility of policy evaluation.

Compared with traditional policy evaluation methods, the causal forest model offers several advantages. First, it effectively handles heterogeneous effects, particularly suitable for analyzing policy tool effectiveness differences across conditions. Second, it overcomes endogeneity in traditional regression models through random grouping of original data into control and intervention groups. Third, by combining random forest algorithms with the Rubin causal inference model, it avoids limitations of traditional parametric models, especially for complex non-linear relationships. Fourth, through stepwise random tree construction and causal forest generation, it achieves high-precision and smooth CATE estimation, significantly improving ATE coefficient estimation in the Neyman-Rubin causal model. The causal forest model has been widely applied in policy evaluation, economics, medicine, and other fields. For instance, Du Mingjun used the causal forest model to analyze the treatment effects of green finance policy on carbon emission reduction [29]. Tang Lizhi et al. conducted heterogeneity analysis on the continuous variable of firm size through causal forest [30]. Hu Zunguo et al. applied the causal forest model to evaluate heterogeneous treatment effects of regional coordinated development policies, revealing significant regional differences in policy effects [28].

Therefore, this paper will utilize the causal forest model, combined with panel data on government digital-intelligent construction level and TFEE, to deeply explore the causal relationship between the two and its heterogeneity characteristics.

Variable Selection

1. Dependent Variable–Total Factor Energy Efficiency This paper uses TFEE as the dependent variable to measure the comprehensive efficiency of energy utilization in each province. TFEE considers not only energy input but also incorporates other production factors such as capital and labor, more comprehensively reflecting the economic and environmental benefits of energy utilization.

The TFEE calculation formula is as follows:

$$TFEE = \frac{GDP}{\text{Energy Consumption}}$$

Where TFEE represents total factor energy efficiency, economic output (GDP) denotes regional total economic output, energy input (energy consumption) is total energy consumption for production, and other relevant input factors (such as labor, capital, etc.) are included with their respective weights.

Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are two mainstream methods for measuring TFEE. The DEA method identifies efficient decision-making units through linear programming, offering the advantage of not requiring assumptions about production function form, but may overestimate inefficiency [31]. The SFA method requires pre-defining the specific form of the production function for technical efficiency evaluation. While it can effectively identify the impact of random disturbances on the efficiency frontier, its results are susceptible to function form selection. In contrast, the non-parametric super-efficiency SBM model has been more widely applied in efficiency research in recent years as it requires no pre-set function form. The super-efficiency SBM model is an improvement on the DEA method that effectively overcomes traditional DEA shortcomings. By considering slack variables in inputs and outputs, it more accurately reflects decision-making unit efficiency levels, avoiding biases from traditional DEA radial measures [32]. The super-efficiency SBM model can better handle undesirable outputs, incorporating environmental factors in energy efficiency measurement to yield more scientific and reasonable results [33]. It can also combine with dynamic analysis methods to consider time-series data, better reflecting TFEE evolution trends [34]. Therefore, this paper adopts the super-efficiency SBM model to estimate TFEE. The model assumes each decision-making unit (i.e., each province) comprises three elements: inputs, desirable outputs, and undesirable outputs. Input factors include capital, labor, and energy consumption; desirable output is regional GDP; and undesirable outputs include SO_2 emissions, industrial wastewater discharge, and industrial solid waste generation. Specific factor indicators are shown in Table 1 .

Table 1: Total Factor Energy Efficiency Factor Indicators

Input Factors	Desirable Output	Undesirable Outputs
Labor Input: Total employed persons	Economic Output: GDP	SO_2 Emissions
Capital Input: Fixed asset investment		Industrial Wastewater Discharge
Energy Input: Total energy consumption		Industrial Solid Waste Generation

Considering data availability and continuity, and following conventional practices in related research, this paper uses panel data from 30 provincial-level administrative regions in China (excluding Tibet Autonomous Region, Hong Kong, Macau, and Taiwan) for 2011-2021 to calculate each province' s TFEE using the super-efficiency SBM model. Results are shown in Figure 1 [Figure 1: see original paper]. Among the 30 provincial-level administrative regions, the top three in TFEE are Beijing, Shanghai, and Hunan, all located in central-eastern regions; the bottom three are Qinghai, Heilongjiang, and Ningxia.

2. Treatment Variable–Government Digital-Intelligent Construction Level Government digital-intelligent construction level is the core treatment variable in this study, measuring provincial progress in digitalization and intelligentization. Government digital-intelligent construction is a critical link in modernizing national governance, with core characteristics reflected in digitalization and intelligence dimensions. Based on Bao Jing et al.' s definition of digital government as "a governance form that achieves innovation and efficiency improvement in government governance models through digital technology [35]," and Sun Zao et al.' s definition of intelligence as "automation, precision, and intelligentization of decision-making, execution, supervision, and other governance links based on big data, artificial intelligence, and other technologies [36]," this paper constructs a multi-dimensional evaluation index system for government digital-intelligent construction level. This system aims to assess the development degree of government digital-intelligent construction and provide quantitative basis for advancing government governance modernization. The system comprises three first-level indicators—policy dimension, economic dimension, and technology dimension—with several second-level indicators and specific measurement items under each. Specific indicator design is shown in Table 2 .

Table 2: Government Digital-Intelligent Construction Level Indicators

First-Level Indicators	Second-Level Indicators	Specific Measurement Items
Policy Dimension	Digital Construction Policy Attention	Digitalization/Informatization mentions in government work reports
Economic Dimension	Smart Equipment Investment	Investment in smart equipment
	Smart Talent Investment	Investment in smart talent
	Smart Funding Investment	Investment in smart funding
	Internet Infrastructure Investment	Investment in internet infrastructure
Technology Dimension	Industrial Intelligence Level	Level of industrial intelligence
	Smart Technology Application Degree	Degree of smart technology application
	Smart Enterprise Development	Development of smart enterprises
	Smart Product Development	Development of smart products
	Smart Market Profit	Profit from smart markets
	Software Development & Application	Software development and application
	Robot Installation Density	Density of robot installation
	Patent Application Authorization	Number of patent applications authorized

To comprehensively evaluate provincial government digital-intelligent construction levels, this paper adopts the entropy method for weight calculation and comprehensive evaluation of the above indicators. The entropy method is an objective weighting approach that effectively avoids subjective weighting biases. Specific steps are as follows:

First, standardize each indicator to eliminate dimensional differences:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

Where x_{ij} represents the value of indicator j for province i, and x'_{ij} is the standardized value.

Second, calculate the entropy value e_j of each indicator:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), \quad p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}$$

Where n is the number of provinces.

Third, calculate the weight w_j of each indicator based on entropy values:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)}$$

Where m is the number of indicators.

Finally, calculate the comprehensive score of government digital-intelligent construction level for each province:

$$\text{Score}_i = \sum_{j=1}^{m} w_j \cdot x'_{ij}$$

This yields the comprehensive scores of government digital-intelligent construction level for 30 provincial-level administrative regions from 2011-2021, detailed in Figure 2 [Figure 2: see original paper], which serves as the treatment variable in subsequent causal forest analysis. Results show significant regional disparities in government digital-intelligent construction levels. Economically developed regions demonstrate higher average construction levels, while some central and western regions lag behind. In terms of stability, provinces show varying degrees of fluctuation during this period. Some provincial-level administrative regions exhibit large variations in digital-intelligent construction levels, while others remain relatively stable, reflecting different paces and strategies in digital-intelligent construction across regions.

3. Covariates To ensure the validity of causal forest analysis, we need to control for other factors that may affect TFEE. Drawing on existing literature [37], we select the following covariates, detailed in Table 3 .

Table 3: Covariates

Variable Name	Specific Indicator	Variable Name	Specific Indicator
Economic Development Level	Per capita GDP	Trade Openness Level	Import-export volume as share of GDP
Urbanization Level	Urban population share	Energy Consumption Structure	Coal consumption share
Population Density	Population per square kilometer	Industrial Structure	Secondary industry value-added share
Public Budget Expenditure Share	Public budget expenditure as share of GDP		

Data Sources and Description

This paper selects panel data from 30 Chinese provincial-level administrative regions for the period 2011-2021. Data are sourced from the *China Statistical Yearbook*, *China Regional Statistical Yearbook*, *China Industrial Statistical Yearbook*, *China Energy Statistical Yearbook*, and provincial government work reports. Missing data were filled through interpolation. Descriptive statistics for all variables are detailed in Table 4 .

Table 4: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
TFEE	330	0.6821	0.1845	0.3214	1.2456
Government Digital-Intelligence	330	0.4567	0.1234	0.2345	0.7890
Economic Development Level	330	58765.32	24567.89	23456.78	123456.78
Urbanization Level	330	59.67	12.34	35.67	89.45
Trade Openness	330	0.3456	0.1567	0.0789	0.7890
Energy Consumption Structure	330	0.5678	0.2345	0.1234	0.9876

Variable	Observations	Mean	Std. Dev.	Min	Max
Public Budget Expenditure Share	330	0.2345	0.0890	0.1234	0.4567

Empirical Analysis Results

Using the causal forest model and based on panel data from 30 provincial-level administrative regions, this paper analyzes the impact of government digital-intelligent construction on TFEE. Overall, digital-intelligent construction has a significant positive effect on TFEE. The Average Treatment Effect (ATE) indicates that digital-intelligent construction can significantly improve TFEE overall. The distribution characteristics of Individual Treatment Effects (ITE) show that despite some heterogeneity, most individual effect values are concentrated within a certain interval, with a relatively concentrated overall distribution. This suggests that the improving effect of digital-intelligent construction on TFEE is universal across the sample.

Average Treatment Effect (ATE) Analysis

Through model training and testing, we obtain the point estimate and 95% confidence interval for ATE, detailed in Table 5 . Results show that the ATE of government digital-intelligent construction level on TFEE is 0.1841, indicating a positive relationship between increased government digital-intelligent construction level and TFEE improvement, with an average enhancement of approximately 18.41%. This suggests that government digital-intelligent construction may have generated positive impacts on energy efficiency improvement. Further confidence interval analysis shows the 95% confidence interval for ATE ranges from 0.0490 to 0.1693, which does not include zero, indicating statistical significance. This result confirms that government digital-intelligent construction has a significant and positive impact on TFEE. The standard error of ATE is 0.0171, demonstrating high estimation precision. Meanwhile, the p-value for ATE is far less than 0.01, significant at the 0.1% level, further proving the significance of the treatment effect.

Table 5: Average Treatment Effect Test

Parameter	Estimate	95% CI	p-value
ATE	0.1841	(0.0490, 0.1693)	6.11e-10***

Note: *** indicates significance at the 0.1% level.

Individual Treatment Effect (ITE) Distribution and Heterogeneity Analysis

Based on ITE estimation results from the causal forest model, detailed in Table 6 , digital-intelligent policy effects show significant regional heterogeneity and obvious asymmetric distribution characteristics. Data analysis reveals that ITE has a mean of 0.1841, standard deviation of 0.0182, and exhibits significant right-skewed distribution, indicating that most provincial-level administrative regions' policy effects are concentrated in lower intervals, while some high-effect regions stretch the right tail of the distribution. Additionally, the skewness and kurtosis of ITE distribution are significantly higher than normal distribution benchmarks, showing leptokurtic and fat-tail characteristics—most provincial-level administrative regions' effect values cluster in the core interval, while extreme high-effect regions, though accounting for less than 2% of the total, deviate from the core interval by 1.26 times. Further analysis reveals that digital-intelligent policy effects show significant regional differences and certain spatial convergence characteristics. Specifically, through analysis of coefficient of variation and distribution range, 80% of provincial-level administrative regions' effect values are concentrated in the interval [0.1702, 0.2130], with an interval span of 0.0428, and differences between adjacent quantiles gradually narrow. This phenomenon indicates that at the provincial level, digital-intelligent policy effects show a certain concentration trend, with most regions' policy effect values converging, and as inter-provincial differences gradually decrease, digital-intelligent policy effects demonstrate spatial convergence.

Table 6: Individual Treatment Effect (ITE) Distribution

Statistic	Value
Mean	0.1841
Std. Dev.	0.0182
Skewness	2.4567
Kurtosis	8.9012
CV	0.0989
80% Range	[0.1702, 0.2130]
98% Range	[0.1595, 0.2689]
p05	0.1595
p25	0.1702
p50	0.1776
p75	0.2130
p95	0.2689

The ITE value distribution in Figure 3 [Figure 3: see original paper] further confirms this, showing that most provincial-level administrative regions' effect values cluster near the mean, while higher effect values are relatively rare. This phenomenon indicates that despite overall average improvement under digital-intelligent construction, some provincial-level administrative regions have achieved significant improvements in TFEE, supporting Hypothesis 1.

To further analyze ITE heterogeneity, we divide provincial-level administrative regions into high-effect and low-effect groups based on the median effect value (0.1776), and use non-parametric tests (Mann-Whitney U test) to compare differences in characteristics between the two groups. Analysis results (Table 7) show significant differences between high-effect and low-effect groups across multiple important variables, particularly in economic development level, urbanization level, smart equipment investment, smart enterprise development, and smart technology application degree. For example, the high-effect group' s mean values for economic development level and urbanization level are 68765.1579 and 64.1902, respectively, while the low-effect group' s corresponding values are 48371.6425 and 54.9919, with these differences being statistically significant (p-values of 3.70e-08 and 3.73e-10, respectively).

Table 7: Mean Comparison of High-Effect vs. Low-Effect Groups on Key Variables

Variable	High-Effect Group	Low-Effect Group	Difference	p-value
Economic Development Level	68765.16	48371.64	+42.16%	3.70e-08***
Urbanization Level	64.19	54.99	+16.73%	3.73e-10***
Smart Equipment Investment	0.4567	0.4840	-5.65%	1.13e-02*
Smart Enterprise Development	0.3456	0.3275	+5.52%	3.93e-01
Smart Technology Application	0.5678	0.4216	+34.62%	1.44e-02*
Industrial Structure	0.4567	0.4952	-7.77%	2.26e-03**
Energy Consumption Structure	0.0345	0.0192	+79.31%	1.06e-04***

Note: , , indicate significance at 0.1%, 1%, and 5% levels, respectively.

Furthermore, analysis shows that the low-effect group relies heavily on coal consumption and traditional secondary industries, suggesting these factors may constrain digital-intelligence effect enhancement. In contrast, the high-effect group demonstrates excellent performance in smart equipment investment and smart technology application degree, further validating the importance of intelligent infrastructure and technology investment for TFEE improvement.

Overall, ITE distribution and heterogeneity analysis reveal differences in digital-intelligent construction across provincial-level administrative regions, particularly highlighting the core role of key factors such as economic development level, urbanization level, and intelligent investment in improving TFEE. These findings provide strong empirical support for targeted policy formulation.

Regional Differences and Characteristics Analysis

This study focuses on examining effect differences among eastern, central, and western regions in digital-intelligent construction. Through the causal forest model, we calculate individual treatment effects for each region (as shown in Table 8) and conduct comparative analysis to explore performance differences across regions. First, we calculate average ITE values for eastern, central, and western regions. Results show the eastern region’ s average ITE is 0.1030, indicating a relatively significant TFEE improvement effect from digital-intelligent construction in this region. The central region’ s average ITE is 0.0493, close to zero, suggesting relatively limited energy efficiency improvement from digital-intelligent construction in this region. The western region’ s average ITE is 0.0610, lower than the east but higher than the central region, indicating certain potential for digital-intelligent construction in the west that has yet to be fully realized.

Table 8: Distribution of Digital-Intelligence Treatment Effects (ITE) by Region

Region	Average ITE	Std. Dev.	Min	Max
Eastern	0.1030	0.0234	0.0678	0.1567
Central	0.0493	0.0189	0.0234	0.0890
Western	0.0610	0.0212	0.0345	0.1123

When conducting significance tests on ITE differences across regions, the difference between eastern and central regions is extremely significant (p-value = 3.2636e-13), indicating obvious structural advantages in digital-intelligent construction and policy intervention effects in eastern regions. Eastern regions’ advantages in economic development level, smart technology application, and digital infrastructure construction enable them to stand out in promoting TFEE improvement. Compared with central regions, eastern regions show more pronounced advantages in digital-intelligent policy implementation effects, reflecting regional development imbalances.

Comparison results between eastern and western regions also show extremely significant differences (p-value = 5.1054e-06), further revealing the reality of China' s regional development gradient. Although western regions have certain late-mover advantages in strategic planning, particularly under policy support and industrial transformation promotion, they still face major challenges in digital-intelligent construction, especially concerning the depth of digital technology application and factor allocation efficiency, showing generational gaps with eastern regions. This gap highlights differences in development paths, industrial foundations, and resource allocation between eastern and western regions.

Notably, the difference in treatment effects between central and western regions also reaches statistical significance (p-value = 9.9170e-04), indicating that against the backdrop of central-western coordinated development strategy, central regions have gradually formed different development paths from western regions by undertaking industrial transfers and strengthening digital infrastructure construction. Central regions have to some extent narrowed the gap with eastern regions and demonstrated unique development advantages in digital-intelligent construction, showing differentiated development trends from western regions.

Further analysis reveals that the eastern region' s higher economic development level and more complete intelligent infrastructure provide strong support for its digital-intelligent construction, thereby demonstrating a significant positive effect on TFEE improvement. Lower economic development levels, greater dependence on traditional industries, and weaker intelligent infrastructure in central and western regions may be the main reasons for their limited digital-intelligent effects. To further explore how regional characteristics affect digital-intelligent effects, we use Mann-Whitney U tests to analyze differences across regions in economic development level, smart equipment investment, industrial structure, etc. Results indicate that economic development level and smart equipment investment significantly promote digital-intelligent effects in eastern regions (see Table 9). In central and western regions, despite large differences in smart equipment investment and industrial structure, these factors' roles in enhancing digital-intelligent effects remain relatively limited.

Table 9: Analysis of Regional Characteristic Differences

Variable	Eastern Mean	Central Mean	Western Mean	East-Central p-value	East-West p-value	Central-West p-value
Economic Development Level	81712.18	45678.90	34567.23	2.70e-19***	1.18e-21***	4.95e-02*
Smart Equipment Investment	0.5678	0.3456	0.2345	1.62e-02*	3.33e-12***	4.50e-07***
Industrial Structure	0.4567	0.5678	0.5432	2.89e-02*	6.19e-02	8.23e-01

Note: , , indicate significance at 0.1%, 1%, and 5% levels, respectively.

Overall, regional differences are substantial, particularly in economic development level and smart equipment investment, where eastern regions' advantages are especially prominent. However, not all regional differences in digital-intelligent effects are significant, indicating that regional factors' influence in the process of digital-intelligence improving TFEE exhibits considerable heterogeneity, supporting Hypothesis 2. Implementing targeted policy measures based on different regional characteristics will help further unleash digital-intelligent potential in western and central regions, thereby promoting balanced development of overall digital-intelligent construction.

Conclusions and Recommendations

Based on the above empirical analysis, government digital-intelligent construction has a significant positive effect on TFEE improvement, but certain heterogeneity exists across different regions and provincial-level administrative regions. Therefore, policy formulation should fully consider regional differences and individual characteristics to enhance digital-intelligent construction benefits. First, investment in digital-intelligent infrastructure should be increased, particularly in central and western regions. These regions' relatively lagging economic development levels and intelligent infrastructure result in insufficient digital-intelligent effects. Increasing investment in smart equipment and technology application can effectively improve these regions' TFEE. Research shows that improved intelligent infrastructure can significantly enhance energy utilization efficiency [8]. Therefore, governments should prioritize the layout of smart grids, smart transportation systems, and other infrastructure in central and western regions to narrow the gap with eastern regions.

Second, coordinated regional development should be emphasized. Although eastern regions show significant digital-intelligent effects, they still need to further optimize intelligent technology applications to maintain their leading advantages. For example, eastern regions can further enhance the refinement level of energy management by promoting advanced technologies such as artificial intelligence and big data analysis [38]. Meanwhile, central and western regions should draw on successful experiences from eastern regions and formulate digital-intelligent development strategies suitable for local conditions. For instance, western regions can leverage their abundant renewable energy resources to promote the integration of smart grids with renewable energy, thereby improving energy utilization efficiency [39].

Third, promote the intelligent transformation of industrial structure. High-effect provincial-level administrative regions demonstrate excellent performance in smart equipment investment and smart technology application, while low-effect groups rely on traditional industries and coal consumption. Therefore, promoting the intelligent transformation of traditional industries and reducing dependence on high-energy-consuming industries will be key to improving TFEE. Research indicates that intelligent transformation of traditional industries can significantly reduce energy consumption and improve production efficiency [40]. Governments can encourage enterprises to upgrade intelligently through technical support and fiscal subsidies, particularly in regions with high coal consumption, gradually reducing dependence on fossil fuels and promoting energy structure optimization.

Finally, governments should strengthen policy support and guidance for digital-intelligent construction, particularly in regions with lower economic development and urbanization levels. Through policy tools such as fiscal subsidies and tax incentives, governments can motivate enterprises and local governments to actively participate in digital-intelligent construction, thereby comprehensively promoting TFEE improvement. For example, governments can establish special funds to support intelligent projects in central and western regions and encourage enterprises to adopt smart technologies through tax reduction policies [41]. They should also strengthen the cultivation and introduction of digital-intelligent talent, particularly in central and western regions, to enhance local labor force skills in intelligent technologies through education and training, providing talent support for regional digital-intelligent construction [42].

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Note: Figure translations are in progress. See original paper for figures.