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How Does New Quality Productive Forces Affect Green Total Factor Energy Efficiency in China? Consider the Threshold Effect of Artificial Intelligence

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Abstract

China's economy is shifting from an era of rapid expansion to one focused on high-quality development, making it imperative to tackle environmental degradation linked to energy use. Understanding how New Quality Productive Forces (NQPF) interact with energy efficiency, along with the mechanisms driving this relationship, is essential for economic transformation and long-term sustainability. This study establishes an evaluation framework for NQPF, integrating technological, green, and digital dimensions. We apply fixed-effects models, the spatial Durbin model (SDM), a moderation model, and a threshold model to analyze the influence of NQPF on Green Total Factor Energy Efficiency (GTFEE) and its spatial implications. This underscores the necessity of distinguishing it from traditional productivity frameworks and adopting a new analytical perspective. Furthermore, by considering dimensions such as input, application, innovation capability, and market efficiency, we reveal the moderating role and heterogeneous effects of artificial intelligence (AI). The findings are as follows: The development of NQPF significantly enhances GTFEE, and the conclusion remains robust after tail reduction and endogeneity tests. NQPF has a positive spatial spillover effect on GTFEE; that is, while improving the local GTFEE, it also improves neighboring regions GTFEE. The advancement of AI significantly strengthens the positive impact of NQPF on GTFEE. AI exhibits a significant U-shaped threshold effect: as AI levels increase, its moderating effect transitions from suppression to facilitation, with marginal benefits gradually increasing over time.

Keywords: green total factor energy efficiency; new quality productive forces; artificial intelligence; spatial spillover effect; threshold effect



Academic Editor: Diego Pablo Ruiz Padillo

Received: 1 July 2025

Revised: 22 July 2025

Accepted: 28 July 2025

Published: 1 August 2025

Citation: Yuan, B.; Gu, R.; Wang, P.; Hu, Y. How Does New Quality Productive Forces Affect Green Total Factor Energy Efficiency in China? Consider the Threshold Effect of Artificial Intelligence. *Sustainability* **2025**, *17*, 7012. <https://doi.org/10.3390/su17157012>

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1. Introduction

The transition to green energy is a fundamental approach to achieving sustainable energy advancement and an important driving force for China's high-quality economic progression. While China's rapid economic development has brought disruptive transformations to society, it has also been accompanied by intensive energy dependence, contributing to a sharp increase in carbon emissions and environmental issues such as the greenhouse effect. Yale University's 2024 Environmental Performance Index (EPI) shows China ranked

156th among 180 nations and territories. The China Energy Development Annual Report (2024) indicates that China's energy consumption continues to grow, reaching a total of 5.72 billion tons of standard coal in 2023, an increase annually of 5.7%, with fossil energy still the main energy sources. Given the tightening resource constraints and an inflexible energy framework, enhancing energy efficiency to curb energy usage has become an urgent need for China. Green Total Factor Energy Efficiency (GTFEE) primarily addresses energy output levels while also stressing the importance of efficiency and sustainability in energy production. It comprehensively integrates various factors such as capital, labor, resources, and the environment, which make it a key benchmark for evaluating the progress of green energy initiatives. Amidst the pressures of economic expansion and energy saving, along with emission reduction goals, improving GTFEE is a necessary way to relieve the pressure.

As the material foundation of socioeconomic development, energy is progressively transitioning into a new stage of deep integration of digital technology and the energy industry. Improving GTFEE and transitioning from a resource-dependent to an innovation-led energy development model require a fundamental shift in the existing productivity paradigm. As a newly emerging policy concept in China's economic discourse, New Quality Productive Forces (NQPF) represents a strategic departure from traditional productivity models, calling for a novel analytical framework to understand its broader implications. NQPF is characterized by digitalization, intelligence, and greenness, aiming to drive sustainable development by innovatively allocating production factors to achieve high-quality economic growth. With global energy transformation and sustainable development, artificial intelligence (AI) is helpful to enhance production efficiency, optimizing energy utilization and promoting green technology innovation. However, technological innovation and AI themselves consume capital and energy, leading to additional inputs for GTFEE while also contributing to environmental pollution, including SO₂ and CO₂ emissions. Therefore, exploring how AI empowers NQPF to improve GTFEE holds substantial practical value in advancing high-quality green development. At the current stage, determining whether the development of NQPF can enhance GTFEE depends on the relationship between its expected benefits, such as economic and environmental gains, and its unintended outputs, including environmental pollution and resource consumption. To address this duality, this study explicitly investigates the conditions under which the benefits of NQPF outweigh the potential costs. Specifically, by integrating undesirable outputs into the GTFEE evaluation framework and examining AI's moderating and threshold effects, we assess how intelligent transformation may reduce such negative externalities. Consequently, revealing NQPF's impact on GTFEE and examining AI's moderating role in this process can provide a scientific basis for policymaking and contribute to sustainable economic development. However, existing studies predominantly focus on linear relationships between indicators, which may overlook the spatial dependence and cross-regional externalities in green energy development. Therefore, this study incorporates a spatial dimension to examine the broader geographic impact of NQPF on GTFEE.

At present, academic research on energy efficiency has attracted widespread attention, with most studies focusing on accurately evaluating energy efficiency and analyzing its spatial and temporal distribution. Regarding influencing factors, the previous literature has primarily explored the effects of technological progress [1,2], financial development [3], urbanization [4,5], and industrial structure [6] on GTFEE. Meanwhile, the previous literature has also focused on exploring the conceptual characteristics of NQPF, mostly adopting qualitative approaches to conduct theoretical analyses. Limited research has analyzed NQPF's impact on economic and social development. Nonetheless, the prior literature has largely emphasized the effects of single dimensions, such as technological innovation and digitization, on energy efficiency and consumption [7]. However, existing studies lack empirical

studies on how the multidimensional combination of NQPF influences energy efficiency. In particular, under the backdrop of rapid AI development, the mechanisms linking AI, NQPF, and energy efficiency remain unclear. Moreover, existing studies predominantly focus on linear relationships between indicators [8], with fewer studies incorporating a three-dimensional spatial perspective [9] to examine GTFEE's spatial dependence and NQPF's spatial influence. Therefore, it is essential to conduct empirical analyses to explore the intrinsic relationships among NQPF, AI development levels, and GTFEE. Doing so can fill theoretical gaps and provide key theoretical support and practical guidance for achieving sustainable energy development.

To achieve this objective, we adopt panel data from 30 Chinese provinces (2011–2022) to systematically explore the multidimensional effect and underlying mechanisms of NQPF on GTFEE. As shown in Figure 1, the main research contents are as follows: (1) We construct an NQPF, AI, GTFEE indicator system and use the entropy weight method to quantify NQPF and AI levels and use Super-SBM to assess GTFEE. (2) We construct both static and dynamic fixed-effects models to systematically explore the effect of NQPF on GTFEE. (3) We use SDM to examine whether NQPF development induces spatial spillover effects on GTFEE in adjacent regions, as well as to measure the intensity of such effects. (4) We construct moderation and threshold effect models to analyze how NQPF's impact on GTFEE varies across different levels of AI development.

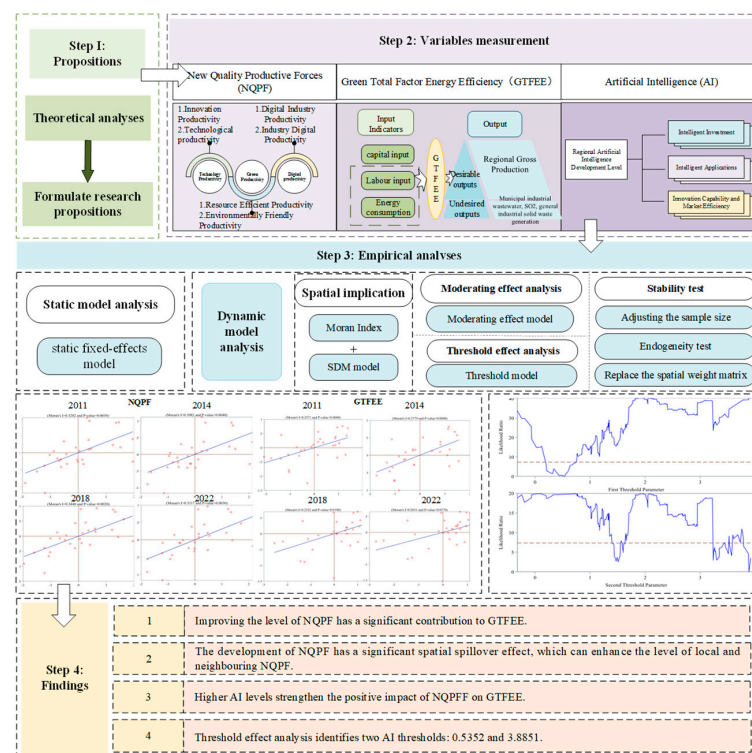


Figure 1. Research structure.

Research Innovations and Academic Contributions: (1) From the perspective of NQPF, this study innovatively examines static and dynamic effects of NQPF development on GTFEE, offering a novel analytical perspective for advancing urban green development. The conclusions are helpful to further understand the effect of NQPF on GTFEE, thereby assisting governments in formulating relevant policies. (2) Considering the spatial externalities of NQPF, this study extends the conventional two-dimensional regional impact framework to a three-dimensional cross-regional analysis, investigating the spatial spillover effects of NQPF in overcoming geographical and economic distance constraints on GTFEE, thereby

broadening the research scope from a geographical perspective. (3) Within the context of artificial intelligence, this study elucidates AI development levels' role in shaping the impact of NQPF on GTFEE. (4) This study further refines the understanding of variations in impact intensity across different AI threshold intervals through threshold effect analysis, thereby identifying the critical nodes and providing empirical evidence of inflection points in the relationship between NQPF and GTFEE. This establishes a theoretical foundation for delineating the boundary conditions of the impact mechanism and enables enterprises and policymakers to determine the optimal range for maximizing marginal returns on resource investments under specific conditions, thereby optimizing energy and technological inputs. These findings provide new insights into existing research.

The subsequent sections are as follows: Section 2 is theoretical analysis. Section 3 is variable definition. Section 4 is analysis of empirical results. Section 5 is the discussion. Section 6 is the conclusion.

2. Theoretical Analyses and Hypotheses

2.1. *The Effect of NQPF on GTFEE*

Energy efficiency has become a widely studied and highly relevant topic. Balancing energy efficiency, economic growth, and environmental sustainability is a critical challenge in achieving sustainable development [2]. Essentially, energy efficiency can be explained from both technological [10] and economic perspectives [11]. From an economic standpoint, energy efficiency refers to achieving higher economic output with lower energy consumption, while from a technological perspective, it involves reducing energy consumption through advancements in energy technology. NQPF signifies a shift from traditional resource-dependent productivity to innovation-driven productivity, emphasizing technological advancements and optimized resource allocation to enhance production efficiency and product quality while simultaneously reducing environmental pollution and resource waste. This approach aims to achieve efficient, green, and sustainable development. First, NQPF emphasizes revolutionary technological breakthroughs to drive profound transformations in production methods. These technologies enhance the intelligence and automation of production, significantly improving efficiency [12] while also fostering the emergence of new industries and products, thereby promoting economic diversification and structural optimization. Second, NQPF establishes a novel and coordinated production system by efficiently allocating key production factors, including labor, capital, technology, and data. The optimization of these factors enhances production efficiency while simultaneously improving product quality and value-added benefits. Furthermore, NQPF advocates for green production, reducing environmental pollution and resource waste while aligning economic and environmental benefits. Collectively, these measures significantly improve GTFEE, thereby promoting sustainable green economic development. Thus, we formulate:

H1. *The development of NQPF can enhance GTFEE.*

2.2. *The Spatial Relationship Between NQPF and GTFEE*

In geographically proximate regions, the flow of key factors, including technology, industry, and policy, remains more fluid, enabling spatial spillover effects in NQPF development. First, the core driving force of NQPF is technological innovation. Based on the Technology Diffusion Theory, technological innovation is inherently diffusive and replicable [8], meaning its influence is not confined to a specific region but can be transmitted across regions. For example, emerging technologies (e.g., clean energy technologies, smart manufacturing, and digital management systems) can be spread through market mechanisms, technological cooperation, and talent mobility, thereby expanding their impact

on neighboring regions. Second, the development of NQPF is often dependent on the agglomeration of advanced manufacturing and high-tech industries. According to Alfred Marshall's Industrial Agglomeration Theory, these industries tend to establish tightly integrated upstream and downstream supply chains, facilitating their diffusion to surrounding regions through coordinated industrial development [13]. This process enhances overall production efficiency in neighboring areas while simultaneously improving energy utilization efficiency. Furthermore, in the context of regional cooperation and industrial chain integration, upstream suppliers and downstream enterprises are often influenced by the green production practices of core enterprises [14], leading them to optimize their own energy consumption patterns. Through green supply chain management, large enterprises have put forward more stringent environmental requirements for suppliers, forcing suppliers to adopt more energy-saving and environmentally friendly production methods. This, in turn, generates spillover effects throughout the entire industrial chain. Additionally, the spatial spillover effects of policies related to NQPF play a crucial role in enhancing regional GTFEE. When a particular region enforces stricter environmental regulations, provides subsidies for green technologies, or sets carbon emission constraints to promote the development of NQPF, neighboring regions may adjust their policy frameworks in response to industrial competition, policy coordination, or market demand. This process facilitates green development on a broader scale and contributes to the overall improvement of GTFEE across regions. Thus, we formulate:

H2. *Improving the NQPF level can improve adjacent regions' GTFEE through the spatial spillover effect.*

2.3. The AI Effect of NQPF on GTFEE

AI, as a transformative General-Purpose Technology (GPT) driving the new wave of technological revolution and industrial development, not only reshapes production and daily life but also gives rise to new business models and industrial structures, making it a crucial engine for advancing NQPF. First, AI enhances the quality and efficiency of NQPF by optimizing resource allocation, enabling enterprises to achieve high-efficiency production with lower energy consumption and carbon emissions. For instance, the widespread application of intelligent manufacturing systems, industrial Internet of Things (IoT), and adaptive production technologies enables a more precise matching of energy consumption with production activities, thereby reducing energy waste and improving energy utilization efficiency. This not only enhances production efficiency but also lowers environmental costs, promoting green and sustainable development. Second, according to the Endogenous Growth Theory, AI accelerates the diffusion and application of green technological innovations [15], thereby empowering NQPF. For example, intelligent energy management systems can monitor and optimize energy use in real time, decreasing unnecessary energy losses. Additionally, AI-driven pollution-monitoring technologies enhance environmental risk warning capabilities, helping enterprises better control emissions, and facilitating the transition to cleaner production models. Furthermore, AI contributes to data-driven decision-making, promoting personalized energy solutions at both regional and industrial levels, thereby amplifying the positive impact of NQPF on GTFEE. Leveraging big data analytics and AI algorithms, governments and enterprises can formulate more precise energy-saving and emission-reduction policies, achieving differentiated management and enhancing policy effectiveness. In summary, AI not only improves the efficiency of NQPF but also plays a crucial role in green technological innovation, intelligent decision-making, and energy optimization, further influencing the impact of NQPF on GTFEE. Thus, we formulate:

H3. Improving the AI level can positively moderate the effect of NQPF on GTFEE.

3. Methods

3.1. Variable Definition

3.1.1. Explanatory Variable

New Quality Productive Forces. Existing studies mainly examine the influence of traditional productivity determinants [16,17] and technology [18] on energy. In contrast, this study examines the effect of NQPF, a novel productivity system, on GTFEE. Unlike traditional productivity, NQPF is primarily driven by technological innovation, digital transformation, and intelligent automation. Its core lies in optimizing and efficiently utilizing production factors through high-tech advancements such as AI, big data, and the IoT, thereby achieving higher production efficiency and sustainable development goals. To rigorously and accurately assess China's NQPF levels, we construct a comprehensive evaluation system grounded in rationality, scientific rigor, and data availability. As Table 1 shows, NQPF is measured across three dimensions: technological productivity, green productivity, and digital productivity, which are further divided into six sub-dimensions, including innovation productivity, technological productivity, and resource-efficient productivity. A total of 18 indicators are used to establish the NQPF evaluation index system. We employ the polarization method to eliminate variable outline effects and variation range, while the entropy weight method is used to compute the NQPF level.

Table 1. NQPF indicator system.

Primary Level	Secondary Level	Tertiary Level	Explanation	Unit	Attribute
Technological Productivity	Innovation Productivity	Innovation Research	Number of domestic patent authorizations	Count	+
		Innovation Industry	Revenue from high-tech industry businesses	CNY 10,000	+
		Innovation Products	Innovation experience of large-scale industrial enterprises	CNY 10,000	+
	Technical Productivity	Technical Efficiency	Labor productivity of large-scale industrial enterprises	%	+
		Technical R&D	Full-time R&D personnel in large-scale industrial enterprises	h	+
		Technical Production	Density of initial installation of industrial robots	%	+
Green Productivity	Resource-Efficient Productivity	Energy Intensity	Energy consumption per unit of domestic production value	%	—
		Energy Structure	Consumption of chemical energy per unit of domestic production value	%	—
		Water Intensity	Industrial water consumption per unit of domestic production value	%	—
	Environmentally Friendly Productivity	Waste Recycling	Ratio of industrial solid waste recycling to total production volume	%	+
		Wastewater Discharge	Industrial wastewater discharge per unit of domestic production value	%	—
		Air Emissions	Industrial SO ₂ emissions per unit of domestic production value	%	—
Digital Productivity	Digital Industrial Productivity	Electronic Information Manufacturing	Integrated circuit output	10,000	+
		Telecommunication Services	Total telecom business volume	CNY 10,000	+
		Network Coverage	Number of broadband internet access terminals	Count	+
	Industrial Digital Productivity	Software Services	Number of software business employees	People	+
		Digital Information	Optical cable length per unit area	m	+
		E-commerce	E-commerce sales amount	CNY 10,000	+

3.1.2. Dependent Variable

Green Total Factor Energy Efficiency. Referring to Fang et al. (2024) [19], Dai et al. (2024) [17], and Lin et al. (2024) [20], we construct an input–output model to measure GTFEE. Factors are as shown in Table 2. Capital input is measured by fixed capital stock [7]. Labor input is represented by the number of employed individuals in each province, while

energy input is calculated based on the total energy consumption of each province. The desirable output is measured by GDP, which reflects the economic growth benefits derived from energy consumption. The undesirable outputs, representing environmental pollution caused by the production process, are selected based on Shao et al. (2023) [5]. We adopt urban industrial wastewater discharge, SO₂ emissions, and general industrial solid waste generation as pollution indicators. Additionally, referring to Gao et al. (2022), we adopt Super-SBM to effectively calculate GTFEE [7].

Table 2. GTFEE indicator system.

Indicator	Variable	Variable Description
Input Indicators	Capital Investment	Fixed capital stock
	Labor Investment	R&D internal expenditure (CNY 10,000)
	Energy Investment	Number of employed persons
Expected Output	Regional Gross Production	Total energy consumption (10,000 tons of standard coal)
	Industrial Wastewater	Regional gross production value (CNY billion)
Undesirable Output	Industrial Sulfur Dioxide	Total wastewater discharge (10,000 tons)
	Industrial Solid Waste	SO ₂ emissions in exhaust gas (10,000 tons)
	Environmental Pollution	Total generation of general industrial solid waste (10,000 tons)
		Comprehensive environmental pollution index (Entropy Method)

3.1.3. Moderating Variable

Artificial Intelligence Level. Considering the early, mid, and late stages of AI development, we construct an AI index system based on three dimensions: AI investment, AI application, and AI innovation capability market benefits. This system is further subdivided into 13 secondary indicators (as shown in Table 3). AI investment ensures that AI technology receives sufficient resource support for its development and reveals the initial driving forces of AI growth. It is measured through infrastructure development, R&D investment, and talent reserves. AI application focuses on how AI technology transitions from the research phase to actual productivity, particularly in industrial applications and product innovation. It includes indicators such as software development and application, smart product development, smart enterprise growth, and the degree of AI technology adoption. AI innovation capability market benefits further analyze AI technology's market performance, commercialization progress, and contribution to economic growth. This includes indicators such as innovation capability, AI market value-added, AI market profitability, AI market size, and social benefits. We adopt the entropy weight method to calculate the AI level [21].

Table 3. AI indicator system.

Primary Indicator	Secondary Indicator	Measurement Method
Intelligent Investment	Internet Infrastructure Investment	Optical cable length per unit area
	Intelligent Economic Investment	R&D expenditure in high-tech manufacturing
	Intelligent Talent Investment	R&D personnel in high-tech manufacturing
	Intelligent Equipment Investment	Fixed asset investment in telecommunications, software, and information technology services
Intelligent Applications	Software Development and Application	Revenue from software products per capita in industrial enterprises
	Intelligent Product Development	Revenue from embedded systems per capita in industrial enterprises
	Development of Intelligent Enterprises	Revenue from high-tech enterprise owners per capita in industrial enterprises
	Adoption of Intelligent Technologies	Revenue from new products in high-tech industries per capita in industrial enterprises
R&D Output	Innovation Capability	Number of patent applications/R&D personnel
	AI Market Value-Added	Total profits of high-tech manufacturing
	AI Market Profit	AI market value-added/Total employment in high-tech manufacturing
	AI Market Scale	GDP per unit of energy consumption (coal, electricity)
	Social Benefits	Number of patent applications/R&D personnel

3.1.4. Control Variables

Referring to Hao et al. (2023) [22], Li et al. (2021) [23], and Wu et al. (2021) [2], we adopt five control variables: (1) Labor Force Level (LFL): measured by the natural logarithm of employment. (2) Economic Development Level (EDL): measured by the per capita GDP. (3) Research and Development Intensity (RDI): measured by the ratio of internal R&D expenditure to the regional GDP. (4) Fiscal Budget Expenditure (FBE): measured by the general public budget expenditure. (5) Industrial Structure Upgrading (IS): measured by the ratio of the value-added of the tertiary sector to the secondary sector.

3.2. Data Source

We select panel data from 30 provinces (excluding Xinjiang) in China from 2010 to 2022. The data are sourced from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, and various provincial statistical yearbooks. Missing data are supplemented using the linear interpolation method [24]. To avoid multicollinearity, we use the Variance Inflation Factor (VIF) to test explanatory and control variables. The results show that all VIF values are below 10, and tolerance values exceed 0.1, suggesting that multicollinearity is not a concern. The descriptive statistics are shown in Table 4.

Table 4. Descriptive statistics.

Category	Variable	Explanation	Mean	SD	Min	Max
Dependent Variable	GTFEE	Green Total Factor Energy Efficiency	0.855	0.274	0.101	1.295
Independent Variable	NQPF	New Quality Productive Forces	0.122	0.120	0.014	0.767
Moderating Variable	AI	Artificial Intelligence Level	11.208	10.493	0.337	61.846
	EDL	Economic Development Level	61,536.09	30,331.66	16413	190,313
	LFL	Labor Force Level	7.591	0.787	5.545	8.864
Control Variables	RDI	R&D Intensity	0.018	0.012	0.004	0.068
	FBE	General Fiscal Budget Expenditure	5457.913	3125.171	705.910	18,533.080
	IS	Industrial Structure	1.272	0.719	0.554	5.297

4. Results and Analysis

4.1. Benchmark Regression

4.1.1. Static Model Analysis

The White test indicates the presence of heteroscedasticity in the short-panel data. Therefore, the clustered robust standard error method is applied for correction. In model selection, the robust Hausman test consistently rejects the null hypothesis and shows that a fixed-effects model should be used [7]. Accordingly, we construct:

$$\ln \text{GTFEE}_{it} = \alpha_0 + \alpha_1 \ln \text{NQPF}_{it} + \alpha_2 \ln \text{CV}_{it} + u_i + v_t + \sigma_{it} \quad (1)$$

where CV represents the control variables. α is the coefficient value. i is city, t is year, u captures individual fixed effects, v accounts for time fixed effects, and σ represents the random error term.

In the regression analyses in this paper, the 1% and 5% significance levels were determined by statistically testing whether the p-values were less than 0.01 and 0.05. The regression results are presented in Columns (1) and (2) of Table 5. Significance levels at 1% and 5% are based on p-values below 0.01 and 0.05, respectively. The coefficients of $\ln \text{NQPF}$ are significantly positive, indicating that NQPF development enhances GTFEE. Specifically, Column (1) reports a coefficient of 0.196 for $\ln \text{NQPF}$ ($t = 4.90$), significant at the 1% level, suggesting that a 1% increase in NQPF is associated with a 0.196% increase in GTFEE. In Column (2), after controlling for additional covariates, the coefficient rises to

0.238 ($t = 2.51$), significant at the 5% level. Although the significance level declines slightly, the result remains robust ($p < 0.05$), supporting the conclusion that NQPF development has a stable and positive impact on GTFEE. Thus, H1 is supported. The possible reasons are as follows: First, technological innovation is one of the core elements of NQPF. It includes the application of green technology, digital technology, and intelligent manufacturing. These technological advancements improve energy utilization efficiency, reduce waste, and enhance resource allocation through more efficient energy management systems, thereby increasing GTFEE. Second, the improvement of NQPF levels promotes industrial structure upgrading, gradually transforming traditional high-energy-consumption and low-efficiency industries into high-value-added and low-energy-consuming green industries. In this process, technology-intensive and intelligent manufacturing industries replace resource-intensive industries [25], leading to an optimized energy consumption structure and consequently enhancing GTFEE. Third, NQPF utilizes big data, blockchain, and new energy technologies [26]. It has promoted changes in production methods; reduced energy, labor, and land inputs and undesirable outputs; and increased economic, social, and environmental benefits, thus increasing GTFEE.

Table 5. Fixed-effects model regression results.

	(1) lnGTFEE	(2) lnGTFEE	(3) lnGTFEE
lnNQPF	0.196 *** (4.90)	0.238 ** (2.51)	0.587 ** (2.12)
L.lnGTFEE			0.266 *** (2.97)
lnEDL		−0.163 (−1.15)	0.155 (1.57)
lnFBE		0.229 (1.7)	0.138 (1.47)
lnLFL		−4.893 *** (−3.34)	−0.640 ** (−2.17)
lnRDI		−0.170 (−1.56)	0.557 ** (2.10)
lnIS		−0.108 * (−1.85)	−0.052 (−1.44)
Constant	1.336 *** (13.60)	10.483 *** (3.36)	5.621 ** (2.50)
Year	Yes	Yes	Yes
City	Yes	Yes	Yes
R ²	0.4887	0.345	0.503

Note: The values in () represent t-values adjusted using clustered robust standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

As shown in column (2) of Table 5, lnLFL's coefficient is −4.893 and is significant at the 1% level, suggesting that the labor force level has a negative impact on GTFEE. When the labor force level increases, GTFEE declines. The possible reasons are as follows: First, when the labor force level increases, especially in high-energy-consuming industries (e.g., heavy industry), each additional worker may require more energy support, thereby increasing energy consumption per unit of output. This could lead to increasing marginal energy consumption benefits, ultimately reducing GTFEE. Additionally, an increase in the labor force may cause imbalances in the industrial structure and the labor market. The additional labor force may not necessarily flow into efficient, green, or technology-intensive industries but may instead expand inefficient and high-energy-consuming industries, such as manufacturing and construction. This can reduce energy utilization efficiency and increase overall energy consumption. Furthermore, lnIS's coefficient is −0.108 and is

significant at 10%, indicating that industrial structure upgrading is negatively correlated with GTFEE. This may be because, although the service industry generally has lower energy consumption, certain sectors such as finance, transportation, and construction remain energy intensive. The advancement of the service industry is often accompanied by the development of infrastructure, transportation, and other related activities, leading to increased energy consumption, which in turn lowers GTFEE. Furthermore, China's industrial upgrading is still in a transitional phase, and the early stages often involve large-scale infrastructure construction, equipment updates, and industrial restructuring, all of which are capital- and energy-intensive. Additionally, some fast-growing service sectors, such as logistics and data services, exhibit high energy intensity, contributing to the observed decline in GTFEE during this phase.

4.1.2. Dynamic Model Analysis

Considering that the development of NQPF may have cumulative and lagged effects on GTFEE, we introduce a one-period lagged term of GTFEE into Model (1) and construct a dynamic fixed-effects model [9]:

$$\ln \text{GTFEE}_{it} = \alpha_0 + \alpha_1 \ln \text{NQPF}_{it} + \alpha_2 \ln \text{CV}_{it} + \alpha_3 L. \ln \text{GTFEE}_{it-1} + u_i + v_t + \sigma_{it} \quad (2)$$

where $L. \ln \text{GTFEE}$ represents the first order lagged term of GTFEE, while other variables are the same as in Model (1).

The regression results are shown in column (3) of Table 5. $L. \ln \text{GTFEE}$'s coefficient is significantly positive at 1%, suggesting that GTFEE exhibits dynamic persistence. The improvement in energy efficiency is generally a long-term cumulative process, relying on past technological upgrades, industrial structure adjustments, and policy guidance. Therefore, a higher energy efficiency level in the previous period has a sustained impact on the current period. Additionally, $\ln \text{NQPF}$'s coefficient is significantly positive at 5%, with a marginal effect of 0.587, indicating that NQPF can significantly enhance GTFEE. Thus, when considering dynamic effects, the findings further support H1.

4.2. Spatial Effects

4.2.1. Spatial Correlation

We adopt Moran's I to determine the spatial correlation between GTFEE and NQPF and adopt an economic–geographical nested matrix as a spatial weight matrix, which simultaneously considers economic factors and geographical distance. The formula is as follows:

$$S^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2, \text{ Moran's } I = \frac{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n \omega_{ij}} \quad (3)$$

$$\omega_{ij} = \begin{cases} \frac{1}{|\text{avgdp}_i - \text{avgdp}_j|}, & i \neq j \\ 0, & i = j \end{cases} \quad (4)$$

where X refers to the observed value of the variable for a given region. $\bar{x}$ is the mean of the variable across all regions. i and j represent cities, S^2 represents sample variance, ω_{ij} represents the economic–geographical nested matrix, and avgdp refers to the average per capita GDP of a city.

The Moran's index plot for NQPF is shown in Figure 2. The Moran's I value for all four years is significantly positive at 1% [27]. The majority of cities' Moran's I values

fall within Quadrants 1 and 3, demonstrating a significant “high–high” and “low–low” clustering effect. This indicates that the spatial correlation of NQPF is positive [28].

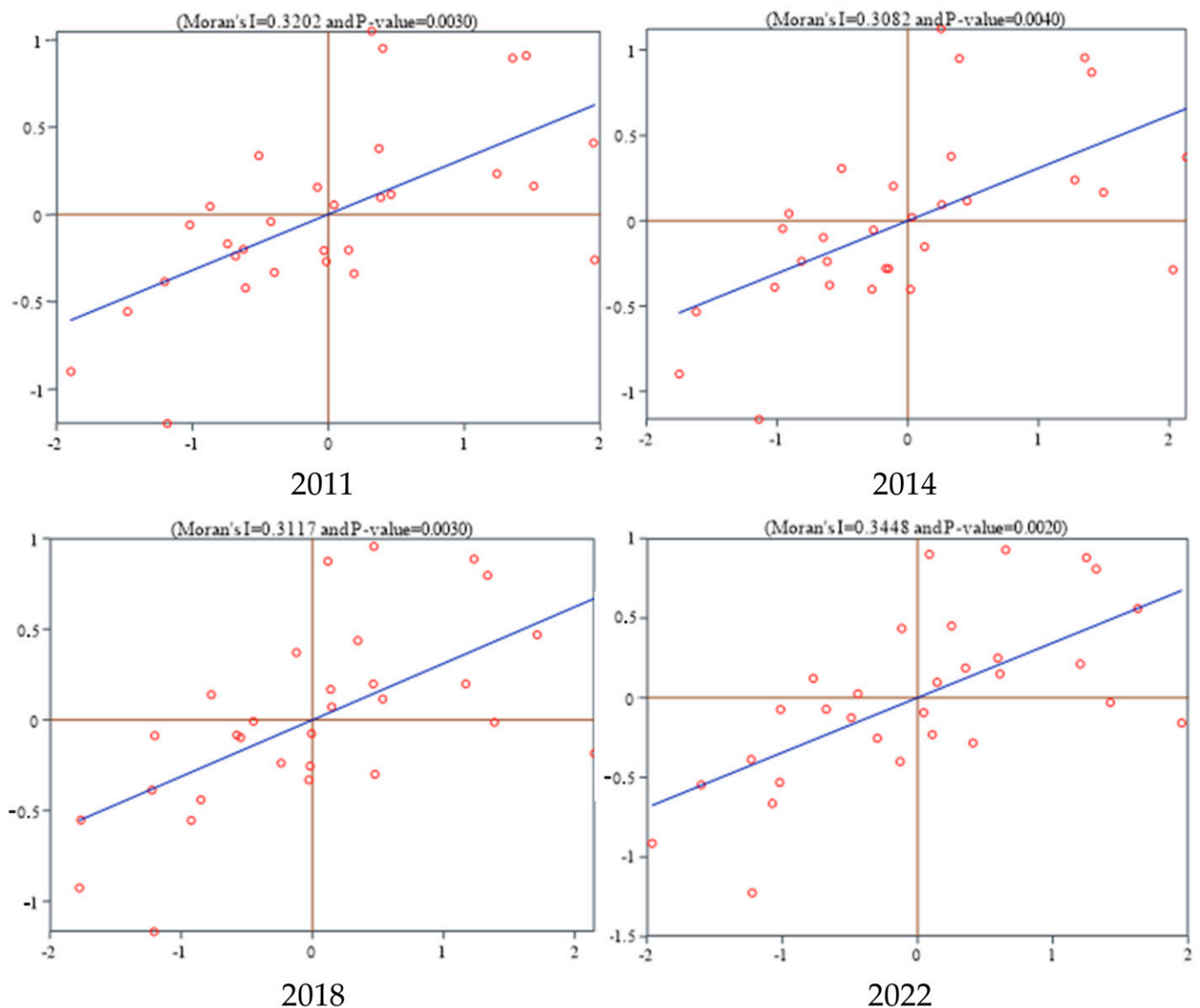


Figure 2. NQPF's Moran scatter plot.

The Moran's index plot for GTFEE is shown in Figure 3. The Moran's I value for all four years is significantly positive at 1%, suggesting that the GTFEE levels of different cities exhibit a positive spatial correlation [29]. Furthermore, the majority of cities' Moran's I values for GTFEE fall within Quadrants 1 and 3, suggesting that cities with high (or low) GTFEE levels tend to be surrounded by cities with similarly high (or low) GTFEE levels. Therefore, GTFEE demonstrates spatial correlation, necessitating the use of a spatial regression model for empirical analysis of its specific impact.

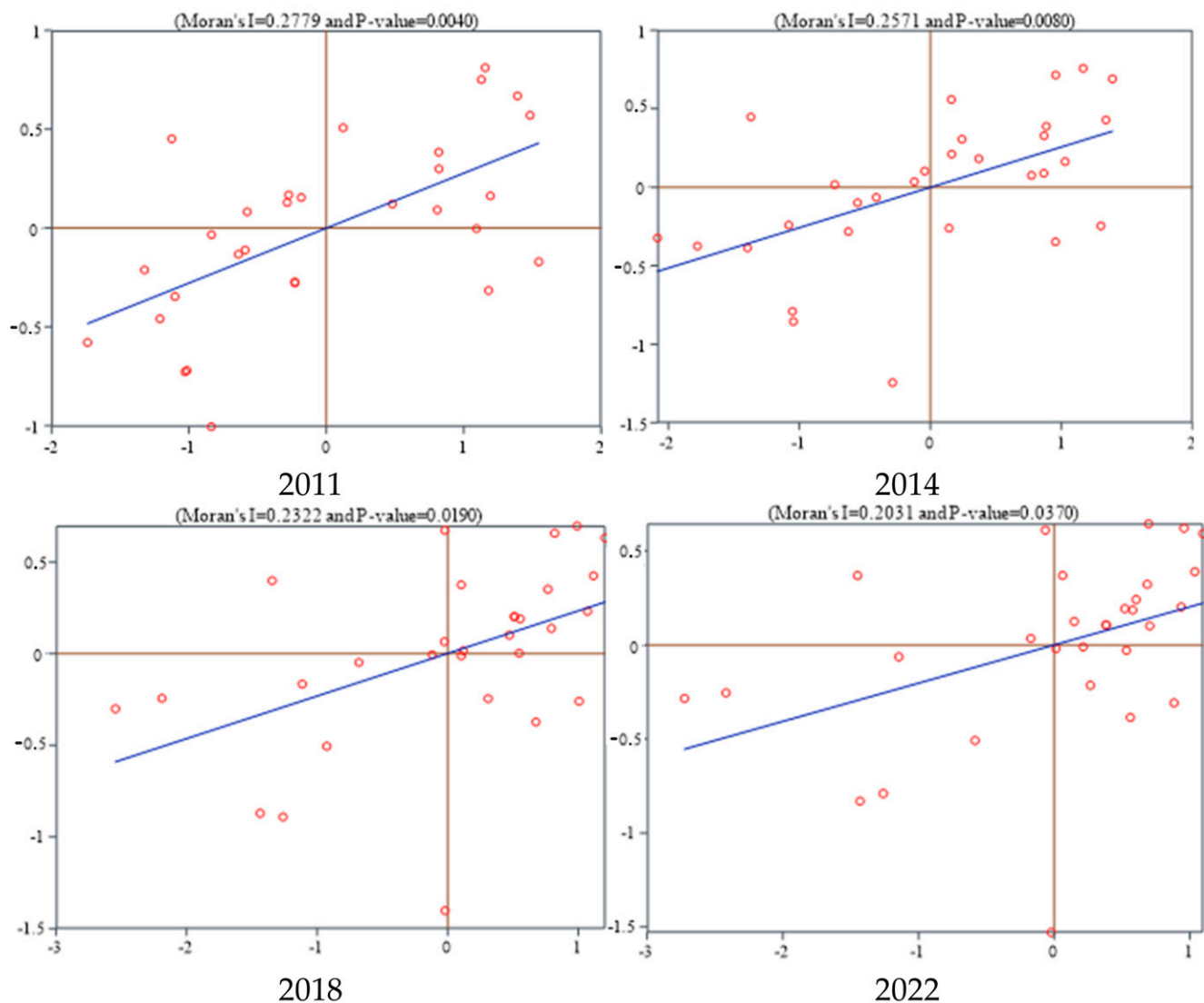


Figure 3. GTFEE's Moran scatter plot.

4.2.2. Spatial Spillover Effect

To further determine the optimal spatial econometric model, this study applies LM, LR, and Hausman tests [21]. The LM test assesses the existence and type of spatial relationships among variables. The LM-Spatial Error and Robust LM-Spatial Error tests are both significant at 1%, while the LM-Spatial Lag and Robust LM-Spatial Lag tests are significant at 5%. These results indicate the simultaneous presence of both spatial lag effects and spatial autocorrelation effects, suggesting that the SDM should be employed for spatial econometric analysis. Through the LR test, both LR-error and LR-lag are significant at 1%, leading to the rejection of the null hypothesis that the SDM can be reduced to a SEM or SLM. The Hausman test is significant at 10%, rejecting the null hypothesis that a random-effects model should be used, thereby confirming that a fixed-effects SDM is the appropriate choice [30].

Accordingly, we construct:

$$\ln GTFEE_{it} = \lambda_0 + \rho W \ln GTFEE_{it} + \lambda_1 \ln NQPF_{it} + \varphi_1 W \ln NQPF_{it} + \lambda_2 CV_{it} + \varphi_2 WCV_{it} + u_i \quad (5)$$

where ρ is the spatial spillover coefficient, λ is the coefficient value, W is the economic-geographical nested matrix, and μ_1 and μ_2 are spatial interaction terms coefficients. The other variables are the same as in Model (1).

The SDM regression results are presented in Table 6. $\ln NQPF$'s coefficient is significantly positive at 1% across all columns, suggesting that enhancing $NQPF$ positively influences both local and neighboring regions' $GTFEE$. This confirms that $NQPF$ development enhances $GTFEE$ through spatial spillover effects, supporting H2. The possible reasons are as follows: First, the development of $NQPF$ is often accompanied by the research and application of advanced technologies, particularly clean energy and environmental protection technologies. These technologies may diffuse to neighboring regions through technology spillover effects, thereby improving energy utilization efficiency in surrounding areas. Second, regions that seek to promote $NQPF$ typically implement a series of green economic policies. These policies may create demonstration effects, encouraging neighboring regions to adopt similar measures, thus improving their $GTFEE$. Additionally, the development of $NQPF$ fosters synergies along the green economic industrial chain. Neighboring regions, through collaboration with core regions, may benefit from greener supply chain management and more efficient energy utilization practices, thereby enhancing overall energy efficiency.

Table 6. SDM regression results.

	(1) $\ln GTFEE$	(2) Spatial lag $\ln GTFEE$	(3) Direct $\ln GTFEE$	(4) Indirect $\ln GTFEE$	(5) Total $\ln GTFEE$
$\ln NQPF$	0.362 *** (4.75)	1.106 *** (4.16)	0.333 *** (4.33)	0.912 *** (3.89)	1.246 *** (5.22)
$\ln EDL$	−0.051 (−0.64)	−0.140 (−0.69)	−0.056 (−0.78)	−0.144 (−0.81)	−0.200 (−1.23)
$\ln FBE$	0.025 (0.23)	0.185 (0.78)	0.031 (0.28)	0.153 (0.79)	0.185 (1.00)
$\ln LFL$	−6.334 *** (−6.51)	−3.388 (−1.34)	−6.211 *** (−5.78)	−1.844 (−0.82)	−8.056 *** (−3.32)
$\ln RDI$	−0.033 (−0.49)	0.180 (0.99)	−0.052 (−0.68)	0.170 (0.97)	0.118 (0.60)
$\ln IS$	−0.069 (−0.97)	0.284 (1.23)	−0.076 (−1.20)	0.245 (1.12)	0.169 (0.70)
City R^2			Yes 0.2961		

Note: The values in () represent t-values adjusted using clustered robust standard errors. *** indicates significance at the 1%.

4.3. Moderating Effect

To explore whether AI development levels influence the effect of $NQPF$ on $GTFEE$ [21,31], we construct a moderating effect model:

$$\ln GTFEE_{it} = \beta_0 + \beta_1 \ln NQPF_{it} + \beta_2 \ln AI_{it} + \beta_3 \ln NQPF_{it} \times \ln AI_{it} - c + \beta_4 \ln CV_{it} + u_i + v_t + \sigma_{it} \quad (6)$$

where $\ln AI \times \ln NQPF$ -c represents the decentralized interaction term between AI levels and $NQPF$. β denotes the coefficient value. All other variables remain consistent with Model (1).

The regression results are shown in Table 7. The coefficients of $\ln NQPF$ and $\ln AI \times \ln NQPF$ -c are significantly positive at 5% and 10%, suggesting that enhancing AI levels strengthens the effect of $NQPF$ on $GTFEE$. This validates the validity of H3. Specifically, after incorporating the moderating variable, $\ln NQPF$'s coefficient is 0.267. Comparing this with the coefficient of 0.238 in column (2) of Table 5, the marginal moderating effect of AI on the main effect is 0.029. The possible reasons are as follows: First, AI's powerful data processing and analytical capabilities allow for precise monitoring of energy consumption patterns, enabling optimized energy allocation, reducing energy waste, and enhancing energy utilization efficiency. Second, in the R&D stage, AI accelerates green energy technological breakthroughs within $NQPF$. For example, AI-driven advancements

in solar and wind energy conversion technologies enhance energy transformation efficiency, promoting the efficient utilization of clean energy. Additionally, AI facilitates intelligent monitoring and regulation, enabling energy-efficient upgrades to production processes, thereby reducing energy consumption per unit of output. Thus, leveraging its intelligent advantages, AI strengthens the impact of NQPF on GTFEE through multiple dimensions, including energy allocation, technological innovation, and production optimization, thereby providing strong support for sustainable development.

Table 7. Moderating effect model regression results.

Variables	lnGTFEE	Variables	lnGTFEE
lnNQPF	0.267 ** (2.66)	lnRDI	−0.169 (−1.68)
lnAI	−0.011 * (−1.75)	lnIS	−0.096 (−1.57)
lnAI × lnNQPF-c	0.035 * (1.71)	Constant	9.934 *** (3.48)
lnEDL	−0.105 (−0.74)	Year	Yes
lnFBE	0.279 * (1.97)	City	Yes
lnLFL	−5.058 *** (−3.17)	R ²	0.3647

Note: The values in () represent t-values adjusted using clustered robust standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4. Threshold Effect

Changes in AI levels may lead to a structural shift in the impact of NQPF on GTFEE. Therefore, a threshold effect model is constructed to analyze how the impact intensity of NQPF on GTFEE varies across different AI threshold intervals [32].

$$\ln GTFEE_{it} = \theta_0 + \theta_1 \ln AI_{it} \times I(\ln NQPF_{it} \leq \gamma) + \theta_2 \ln NQPF_{it} \times I(\ln AI_{it} > \gamma) + \sum_{j=3}^T \theta_j CV_{it}^j + u_i + v_t + \sigma_{it} \quad (7)$$

where γ is the threshold value, and θ_1 and θ_2 represent the impact coefficients of NQPF on GTFEE when $\ln AI_{it} \leq \gamma$ and $\ln AI_{it} > \gamma$, respectively. I is the indicator function.

This study applies the Bootstrap method for threshold testing (Table 8). Based on Hansen's (2000) threshold theory, AI levels exhibit a significant double-threshold characteristic, both of which fall within the 99% confidence interval [33]. We used LR tests to verify the validity of the thresholds [34]. As shown in Figure 4, the estimated threshold values are consistent with the actual values, and the LR test is successfully passed. Thus, a double-threshold regression model is constructed.

Table 8. Threshold test results.

Models	Threshold Value	F Test	p-Value	10%	5%	1%
Single threshold	0.5352	38.36	0.00	13.273	14.435	18.315
Double threshold	3.8851	19.29	0.00	11.584	12.778	15.347

The regression results are shown in Table 9. In column (1), when $\ln AI \leq 0.5352$, the positive impact of NQPF on GTFEE is suppressed or even becomes negative. At this stage, low AI levels hinder NQPF's ability to enhance GTFEE effectively due to weak intelligent transformation capacity, limited technological application, and low digital integration. The development of NQPF at this stage may be accompanied by industrial expansion effects, leading to increased energy consumption and pollution, thereby reducing GTFEE. When

$0.5352 < \ln AI \leq 3.8851$, $\ln NQPF$'s coefficient is significantly positive, with a value of 0.029, suggesting that the previous inhibitory effect transitions into a promoting effect. At this stage, AI technology starts penetrating the industrial chain, beginning to exert a positive influence on the impact of $NQPF$ on $GTfEE$. However, the intelligent optimization and automation control brought by AI have not yet fully replaced traditional models, meaning that energy utilization efficiency is still constrained. As a result, the marginal effect on $GTfEE$ remains limited, with a coefficient of only 0.029. When $\ln AI > 3.8851$, $\ln NQPF$'s coefficient is significantly positive, with a marginal effect of 1.209, indicating that a higher level of AI is typically associated with the development of high-end manufacturing and the new energy industry. This transformation reduces the proportion of traditional high-energy-consuming industries, thereby optimizing energy utilization efficiency. Consequently, the positive effect of $NQPF$ on $GTfEE$ becomes significantly stronger.

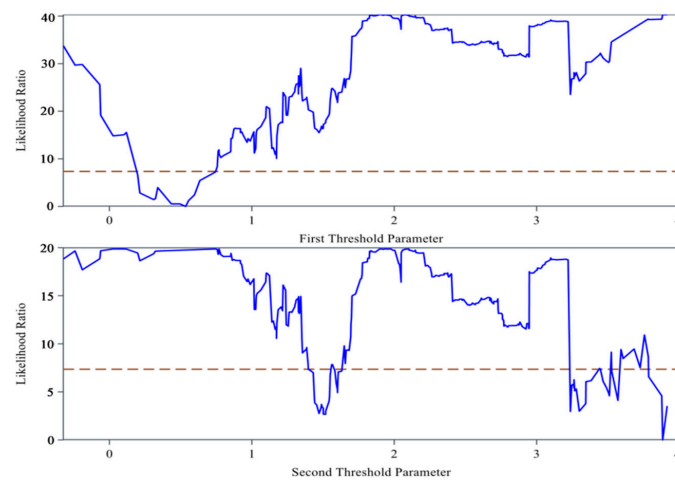


Figure 4. LR test results.

Table 9. Threshold model regression results.

Variables	(1) $\ln GTfEE$	(2) $\ln GTfEE$
$\ln NQPF (\ln AI \leq 0.5352)$	−0.213 *** (−4.89)	0.238 ** (2.51)
$\ln NQPF (0.5352 < \ln AI \leq 3.8851)$	0.029 * (1.81)	
$\ln NQPF (\ln AI > 3.8851)$	1.209 *** (3.87)	
$\ln EDL$	0.554 *** (10.65)	−0.163 (−1.15)
$\ln FBE$	0.450 *** (7.50)	0.229 (1.7)
$\ln LFL$	−0.119 (−0.17)	−4.893 *** (−3.34)
$\ln RDI$	0.312 *** (6.77)	−0.170 (−1.56)
$\ln IS$	0.345 *** (8.97)	−0.108 * (−1.85)
Constant	−10.800 *** (−7.86)	10.483 *** (3.36)
Year	Yes	Yes
City	Yes	Yes
R^2	0.947	0.345

Note: The values in () represent t-values adjusted using clustered robust standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Comparing column (2) of Table 9 (Model 1 regression result) with column (1), it can be observed that although when $\ln AI \leq 3.8851$, the coefficients in column (1) are both smaller than 0.238 in column (2), once $\ln AI > 3.8851$ (i.e., when AI development reaches a relatively mature stage), the comparison between column (1) and column (2) coefficients ($1.209 > 0.238$) indicates that AI significantly enhances the positive impact of NQPF on GTFEE. Thus, from a long-term development perspective, advancing AI has a sustained positive impact on strengthening the effect of NQPF on GTFEE.

4.5. Robustness Tests

We conduct robustness tests using truncation processing, replacement of the spatial weight matrix, and instrumental variable methods for endogeneity testing. The details are as follows:

1. Adjusting sample. Extreme values in the dataset may distort research results. Therefore, all variables undergo a 1% truncation process, where values below the 1st percentile and exceeding the 99th percentile are replaced with the 1st and 99th percentile values, respectively. As in column (1) of Table 10, $\ln NQPF$'s coefficient is positive at 5%, indicating that the regression estimates remain unaffected by the truncation adjustment, confirming the research conclusion is robust.
2. Endogeneity test. To mitigate potential endogeneity issues, this study employs the first-order and second-order lagged terms of NQPF as instrumental variables and applies 2SLS method for estimation [35]. As in column (3) of Table 10, $\ln NQPF$'s coefficient is positive at 1%, the same as the previous conclusions, further validating robustness.
3. Replacing the spatial weight matrix. We replace the economic–geographical nested matrix with a geographical distance matrix for regression analysis. As indicated in (3) to (5) of Table 10, $\ln NQPF$'s coefficient remains significantly positive across all three columns, confirming the research conclusion is robust.

Table 10. Robustness test results.

Variables	Adjusting Sample	Endogenous Test	Replace Spatial Weight Matrix		
	(1) $\ln GTFEE$	(2) 2SLS $\ln GTFEE$	(3) Direct $\ln GTFEE$	(4) Indirect $\ln GTFEE$	(5) Total $\ln GTFEE$
$\ln NQPF$	0.220 ** (2.32)	0.216 ** (2.46)	0.355 *** (4.40)	1.988 *** (4.46)	2.343 *** (5.16)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes		Yes	
City	Yes	Yes		Yes	
R^2	0.296			0.284	

Note: The values in () represent t-values adjusted using clustered robust standard errors. *** and ** indicate significance at the 1% and 5% levels, respectively.

5. Discussion

This study examines the connection between NQPF and GTFEE. Using both static and dynamic models, it explores their connection in depth. The findings show that improving NQPF significantly enhances GTFEE. This conclusion aligns with the findings of Zhao et al. (2024) [36], Wang et al. (2024) [37] and Wu et al. (2024) [38] and also indirectly supports the research of Shah et al. (2022) [39], Cui and Cao (2024) [40], and Zhang et al. (2024) [41]. The results have important practical implications. For energy-intensive industries, increasing investment in NQPF development can facilitate energy conservation and emission reduction objectives [42]. Simultaneously, it bolsters market competitiveness while advancing the industry's transition toward a greener and more efficient model. For policymakers, these insights provide a robust foundation for policy formulation that

fosters NQPF development. Policy guidance can accelerate the integration of NQPF across industries, ultimately leading to an overall improvement in GTFEE at the societal level [43].

Building on the existing literature research and drawing upon the studies of Gu et al. (2023) [21] and Cui and Cao (2024) [40], we extend the research framework from a two-dimensional linear perspective to a three-dimensional spatial analysis. First, the Moran index indicates that both the development of NQPF and GTFEE exhibit positive spatial correlation. They primarily manifest in H-H and L-L clustering patterns, which can enhance the levels of NQPF and GTFEE in both local and neighboring areas [42,44]. This finding is consistent with Gao et al. (2024) [21]. Moreover, SDM regression results show that the development of NQPF can improve GTFEE in adjacent areas through spatial spillover effects, aligning with Wu et al. (2024) [38] and Zhao et al. (2022) [45]. Yin and Shen (2025) [46] and Wang and Chen (2025) [47] provide valuable references for the government in optimizing regional coordinated development strategies and formulating differentiated policies. By revealing the spatial spillover effects of NQPF, this study highlights the importance of regional interconnectivity. This implies that policymakers should focus on promoting resource and technology sharing and cooperation across regions, thereby facilitating the wider diffusion of NQPF and ultimately enhancing GTFEE on a broader scale.

Referencing the research of Zhang and Zhang (2024) [48], we explore the role of AI in amplifying the impact of NQPF on GTFEE. Through moderation and threshold effect tests, the findings reveal that AI levels can strengthen the positive impact of NQPF on GTFEE, confirming the conclusions of Luo et al. (2024) [49] and Wang et al. (2024) [50]. Further analysis shows that AI exhibits a double-threshold effect. As AI levels increase, the impact of NQPF on GTFEE shifts from suppression to promotion, with the effect intensity gradually strengthening over time. AI empowers production processes with intelligence, making technological innovation and resource integration in NQPF development more efficient [38,48,51,52]. This, in turn, facilitates the adoption of clean energy, helping firms and industries optimize their production strategies in response to environmental and market dynamics, thereby improving regional GTFEE.

6. Conclusions and Recommendations

6.1. Research Conclusions

This study explores the multidimensional effect of NQPF on GTFEE and the threshold effect of AI. The findings are as follows:

Static and dynamic fixed-effect models regression analysis indicates that $\ln$ NQPF's coefficients are all significantly positive at 5% levels, with marginal effects of 0.238 and 0.587, respectively. This confirms that the development of NQPF can enhance GTFEE.

According to the SDM regression findings, $\ln$ NQPF's coefficients are significantly positive at the 1% level, demonstrating that NQPF development exhibits a significant spatial spillover effect, which improves both local and neighboring regions' GTFEE.

The moderation effect regression results show that higher AI levels strengthen the positive impact of NQPF on GTFEE, with a marginal moderating effect of 0.029.

Threshold effect analysis identifies two AI thresholds: 0.5352 and 3.8851. When $\ln$ AI $\leq$ 0.5352, AI exerts a suppressive effect on the main effect. However, as AI levels increase, once $\ln$ AI $>$ 0.5352, AI's moderating role shifts from suppression to promotion, and the impact intensity gradually increases. From a long-term perspective, when AI development reaches a high level ($\ln$ AI $>$ 3.8851), it significantly enhances the impact of NQPF on GTFEE.

6.2. Policy Recommendations

In response to the research findings, we present the following recommendations:

- (1) The government should vigorously develop NQPF to assist in improving GTFEE. First, the government should strengthen policy support and guidance, formulate and implement strict industrial upgrading policies, eliminate high-energy-consuming and high-pollution traditional industries, and promote the concentration of resources in green and low-carbon NQPF industries. Additionally, policy measures such as financial incentives and tax reductions should be introduced to support enterprises in the R&D and application of green technologies and intelligent manufacturing. Second, the government should strengthen regional cooperation, implement regional coordination strategies, promote inter-provincial collaboration, develop green economic zones, and encourage resource sharing and green technology diffusion. Furthermore, the government should increase investment in related scientific research by providing government grants or interest-subsidized loans, encouraging enterprises to actively engage in R&D in NQPF-related fields. More funding should be allocated to the development of green energy technologies, new materials, and intelligent manufacturing technologies.
- (2) The government should fully utilize the spillover effects of NQPF to promote inter-regional sharing and mobility of green technologies and resource policies, thereby enhancing overall GTFEE. By establishing a regional collaborative innovation mechanism, the government can facilitate the flow of technology, resources, and policies across different regions. It should support interregional green technology cooperation projects, create shared platforms, and encourage developed regions to transfer successful NQPF experiences and technologies to less developed areas in central and western China, achieving coordinated regional growth. Additionally, the government should encourage enterprises to invest across regions, providing financial and policy support for green technology enterprises to expand into neighboring areas by setting up branches or engaging in cooperative projects. Furthermore, tax incentives should be granted to enterprises and projects that enhance GTFEE through technology spillovers, encouraging them to share technological achievements.
- (3) From a long-term developmental perspective, fully developed AI technology exerts a notable promotive impact on NQPF's effect on GTFEE. Therefore, the government should promote AI development in phases. At the early AI stage, policies should prioritize the establishment of fundamental AI infrastructure, encourage enterprises to adopt AI technology, and mitigate the rise in energy consumption attributed to NQPF expansion. In the mid-AI development stage, the focus should be on supporting AI applications in industrial manufacturing and energy optimization, improving the level of intelligent manufacturing, so that AI's impact on the main effect shifts from negative to positive, truly transforming into a tool for improving energy efficiency. In the mature stage of AI technology, policies should promote AI empowerment for green and low-carbon transformation, build an AI + green energy system, and make AI a core driving force for long-term energy efficiency improvements, thereby maximizing its impact on the main effect. Since different provinces have varied economic development and technological innovation capabilities, the government should formulate targeted AI technology promotion strategies based on each province's characteristics. In the economically developed eastern coastal provinces, where there is already a relatively mature foundation for AI technology R&D and application, these regions can take the lead in advancing the deep application of AI technology in energy management, particularly in industrial production, transportation, and building management, to achieve efficient energy utilization through intelligent technology. To ensure the widespread application of AI technology in enhancing NQPF and GTFEE, in the AI-lagging central and western regions, the government can attract AI

enterprises and research institutions to these areas through financial subsidies and talent introduction policies.

6.3. Research Prospects

Although this study conducts a detailed analysis of the impact of NQPF on GTFEE and reveals a series of important associations and patterns, there remains significant potential for further expansion and deepening due to the complexity and broad scope of this study field. In terms of process mechanisms, future studies can further explore the specific pathways or mechanisms through which NQPF influences GTFEE, for example, key elements of NQPF, such as the application of innovative technologies and transformation of production methods, and how they gradually penetrate and ultimately impact GTFEE at the micro-level of enterprise production processes, the meso-level of industrial structure adjustments, and the macro-level of regional economic development. From a policy impact perspective, future research can further examine the moderating effects of various policy tools, such as financial subsidies, tax incentives, and industrial planning, on the relationship between NQPF and GTFEE. Additionally, further analysis can explore how different policies perform at different development stages and in different economic environments.

Author Contributions: Conceptualization, B.Y., R.G. and Y.H.; methodology, B.Y. and R.G.; software, Y.H.; formal analysis, P.W. and Y.H.; writing—original draft preparation, B.Y. and R.G.; writing—review and editing, P.W. and Y.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the Hebei Academy of Sciences Basic Scientific Research Fees System Pilot Project (Grant number: 2025PF06) and the Social Science Fund of Hebei Province (Grant number: HB24YJ004).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

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

Acknowledgments: The authors are particularly grateful to the editors and reviewers for their most insightful and valuable comments on this paper, which played an important role in improving the quality of the research.

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

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