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Digital Economy, Financial Development, and Energy Poverty Based on Mediating Effects and a Spatial Autocorrelation Model

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Abstract: How to effectively solve the problem of energy poverty from the perspective of digital economy is a topic worthy of attention. As a new economic form characterized by information technology, does the digital economy have an important impact on energy poverty? What is the inner mechanism? Based on the theoretical analysis of the internal mechanism of the impact of the digital economy on energy poverty, this paper systematically investigates the impact of the digital economy on energy poverty by establishing a mediation effect model, spatial autocorrelation test, and heterogeneity analysis, taking 30 provinces in China as the research object. The study found that: (1) the digital economy has a significant mitigation effect on energy poverty, there are regional differences, and the mitigation effect is more obvious under a high level of digital economic development; (2) financial development is one of the mechanisms involved in alleviating energy poverty, and only the intermediary effect in the eastern region is significant; (3) energy poverty has a gradually increasing positive spatial correlation and obvious spatial agglomeration characteristics. Finally, this research provides policy implications for fully realizing the potential of the role of the digital economy and financial development, thereby alleviating energy poverty.

Keywords: digital economy; financial development; energy poverty; mediating effects; spatial autocorrelation

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1. Introduction

Energy is a powerful engine of economic and social advancement as well as a fundamental material need [1,2]. However, energy poverty has emerged as one of the most critical challenges facing the current global energy system, attracting the attention of both governments and researchers. It involves a wide range of issues, such as economic growth, social justice, education, and health, affecting people's well-being and socioeconomic development [3]. Currently, China's energy structure is dominated by coal, with more than 70% of the system being based on it; however, coal combustion suffers from low efficiency and creates environmental pollution, and will certainly pose a threat to sustainable development and exacerbate energy poverty in the long run. According to the International Energy Agency (IEA), energy poverty affected 1.5 billion people globally in 2010. It is estimated that by 2030, 1.4 billion people will lack access to electricity, while the number of those relying on biomass energy will rise to 2.6 billion.

China has made progress in energy production, consumption, system reform, and technology innovation after clarifying the strategic needs of the energy revolution. However, China's energy poverty problem endures under the new circumstances of economic system transition, energy structure transformation, and consumption pattern shift. As the world's largest developing country, China's energy poverty problem is complex and multifaceted, impeding progress towards high-quality growth. Identifying energy poverty in China is crucial for eradicating poverty and ensuring the sustainable development of the economy and environment [4,5].

As a result of the latest wave of industrial and technological revolutions, China has entered the digital economy age. With the development and application of advanced technologies such as big data and the Internet of Things, the potential value of digital information has been continuously explored and the digital revolution has become a new driving force for the development and transformation of various societal fields [6,7]. The digital revolution, which utilizes contemporary network technology as its carrier, contributes to the in-depth integration of modern informatization and the conventional energy industry, propelling the energy industry toward digital and intelligent transformation [8]. The rapid growth of the energy industry increases energy production and supply while encouraging research into the exploitation of new energy sources, providing new choices for alleviating energy poverty. Consequently, what is the evolution characteristic of the digital economy and energy poverty? Can the digital economy mitigate energy poverty? Will different levels of digital economy development have varying effects on energy poverty? What mechanism underlies this mitigation? Will the mitigation effect be regionally and spatially heterogeneous? Moreover, are there spatial autocorrelations in energy poverty? Clarifying the above issues can help us to understand the relationship between the digital economy and energy poverty, and has important practical implications for China's efforts to strengthen the digital economy's effect on reducing energy poverty to ensure energy sustainability.

2. Literature Review

(1) Digital economy and energy use. In the 1970s, under the framework of neoclassical growth theory, scholars represented by Dasgupta and Heal (1979) [9], Solow (1974) [10], and Stiglitz (1974) [11] analyzed the optimal exploitation and utilization paths of resources. Overall, they argued that a sufficiently rapid pace of technological progress can adequately alleviate the constraints of natural resource scarcity and promote the sustainable growth of the economy.

On this basis, technological progress has attracted the attention of scholars to the easing of energy constraints in the process of sustainable economic development. Scientific and technological innovation can change the extensive development mode of high input–high energy consumption and low efficiency while benefitting the transformation of the economy to high-quality development and realizing the transformation of new and old economic momentum. Having entered the era of the fourth scientific and technological revolution based on the knowledge system of the first three industrial revolutions, the digital economy has become more subversive and transformative with the exponential expansion of information systems and digital technologies. The "digital economy", originally proposed by Tapscott (1997) [12], mainly refers to a series of economic activities that are widely used in information and communication technologies. With the deepening of the digital age, the G20 Summit in Hangzhou made an authoritative definition of the digital economy: the digital economy is a kind of social and economic activity with digital technology and information as the core production factor, modern information network technology as the main carrier, and the effective use of information and communication technology as the main driving force to improve production efficiency and optimize the national economic structure. Existing research studies have mostly employed index systems to measure the digital economy [8,13]. Discussion of the economic effects of the digital economy is mainly reflected in the integration of traditional finance and digital technology, which in turn gives rise to the important impact of digital finance on the economy; digital finance can promote technological innovation [14], improve capital mismatch [15], and enhance the synergy between economic development and the ecological environment, thereby promoting the high-quality development of China's economy.

At present, the research on the digital economy and energy utilization mainly focuses on the impact of the digital economy on energy consumption and environmental pollution.

Lange et al., (2020) [16] argued that digitalization can have a dampening effect on energy consumption by improving energy efficiency and optimizing the industrial structure, while the widespread application of digital technology directly increases energy consumption and indirectly causes energy demand, thus producing a growth effect on energy consumption. The digital economy can have a direct impact on carbon emissions through digital technology and inhibit carbon emissions by improving the efficiency of innovation. The innovation power brought by the digital economy can reduce the carbon emissions of enterprises by promoting the intensification and online use of industrial production models, thereby reducing environmental pollution.

(2) Research on energy poverty. Energy poverty has long attracted the attention of scholars at home and abroad, and the relevant literature mainly focuses on the concept, causes, measurement, and improvement path of energy poverty. The concept of "energy poverty" can be traced back to "fuel poverty" in Britain in the 1870s. With the continuous changes in China's economic situation and energy structure, the concept of energy poverty has been further enriched and developed, and now mainly includes four meanings: access to energy services is hindered [17,18], energy needs cannot be met [4,19], lack of ability to pay for energy services [20,21], and difficulties in using clean and advanced energy [22].

There are many causes of energy poverty. Energy poverty is affected by macro-level policies and strategies, energy prices, income levels, and environmental elements [23–27], as well as micro-level household conditions, family structure [28,29], and even more delicate individual social relationships and emotions [19,30]. Scholars have been trying to identify the appropriate indicators and methods for measuring energy poverty, and the 10% indicator and the low income/high cost (LIHC) indicator are widely used [31–33]. As research has advanced, scholars have begun to develop more complete indicator systems for evaluating energy poverty [21,34–36]. Scholars have paid attention to comprehensive energy poverty measurement and analysis of its antecedents and consequences in developing countries [35]. However, the majority of studies that have measured energy poverty in multiple dimensions have been based on contexts in developed countries [37,38].

Scholars have discussed ways to improve energy poverty as well. Surveys by Li et al. (2021) [36] show that areas with lower energy efficiency lack electricity supply, which tends to trap them in energy poverty. In addition, people's long-term dependence on traditional biomass energy can lead to energy scarcity [35]. Improved energy efficiency can alleviate energy poverty, including improving the living conditions and well-being of residents [39], alleviating economic pressures, and reducing the burden of energy consumption. Energy poverty can accelerate the growth of CO_2 emissions [40], although at the same time the low-carbon energy transition can be effective in alleviating energy poverty in China [41]. In addition, rapid development of the renewable energy industry and improved financial inclusion can significantly reduce energy poverty [42,43].

By combing through the existing literature, it can be found, first, that existing research focuses on the impact of technological progress on energy poverty and does not focus on the relationship between the digital economy and energy poverty. Second, the existing literature does not focus on the mechanisms by which the digital economy affects energy poverty, and there is relatively little research on financial development and energy poverty. Third, there is less research on the linear and nonlinear relationship between the digital economy and energy poverty, and the spatial characteristics of energy poverty have not received attention. Based on this, the present paper attempts to construct an index system for the evaluation of digital economy and energy poverty, analyze the effect and mechanism of the digital economy and financial development on energy poverty through the entropy method, spatial autocorrelation method, and intermediary effect model, and consider the nonlinear impact of different digital economic levels on energy poverty, as well as the spatial distribution pattern of energy poverty, thus aiming to improve the current situation of energy poverty for the government in the new situation and provide a beneficial reference for promoting high-quality economic development.

3. Theoretical Analysis

Energy poverty, according to Xu et al., (2020) [44] and Fortier et al., (2019) [45], is defined as difficulties in obtaining and using clean and advanced energy under effective and safe conditions. In conjunction with this concept, this study conducts a theoretical analysis of the digital economy's impact on energy poverty.

3.1. Direct Mechanism of Digital Economy Affecting Energy Poverty

The digital economy has an effect on energy poverty primarily by upgrading energy structures and enhancing energy management. On the one hand, comprehensive digital technology applications can optimize the energy structure. Digitalization propels energy production, operation, and transmission [6,16], which can increase energy production efficiency, decrease energy transaction costs, optimize energy allocation, and prevent excessive energy consumption [8,23]. In addition, widespread use of digital technology promotes regional technological innovation, laying the foundations for higher energy efficiency and accelerating renewable energy transition [46–48]. As the consumption of traditional biomass falls, the transition to a cleaner and greener energy consumption structure contributes to the reduction of energy poverty [13]. On the other hand, digital technology can increase the effectiveness of energy management. By gathering data, intelligent management systems based on information technology can precisely pinpoint the produced energy's use and accurately monitor it. This reduces labor inspection costs and improves the efficiency of energy management and energy use, thus mitigating energy poverty [49,50]. Accordingly, the following assumption is made:

Hypothesis 1 (H1). *The digital economy has a significant mitigating effect on energy poverty.*

3.2. Impact of Different Levels of Digital Economy Development on Energy Poverty

Though the digital economy contributes to less energy consumption, the development of the information and communications technology (ICT) industry itself needs more energy. Therefore, the impacts of different levels of the digital economy on energy poverty may vary considerably. In the early development stages of the digital economy, the construction of digital infrastructure had not been perfected, and there was a certain lag in the application of digital technologies. The improvement in energy efficiency resulting from technical progress is not yet apparent. At the same time, at this stage, supplementary energy production requires the consumption of large amounts of coal and other resources, causing more serious environmental pollution and making it difficult to achieve the effect of alleviating energy poverty in a short period or even aggravating the situation. Due to the constant updating and improvement of digital technologies, their own energy consumption will decrease A digital infrastructure becomes more complete, research and development of technology for new energy becomes more mature [47], energy management is further optimized, and the energy utilization efficiency is vastly enhanced, which together will make the alleviation effect on energy poverty more evident. Accordingly, Hypothesis 2 is proposed:

Hypothesis 2 (H2). *At higher development levels, the digital economy has a more significant mitigating effect on energy poverty.*

3.3. Indirect Mechanism of Digital Economy Affecting Energy Poverty

As the digital economy grows, financial institutions' development trajectory becomes clearer. The digital transformation of financial institutions in the digital era improves the scale, level, and efficiency of financial services, reduces financial risks and financing costs, and boosts the capital market [8,51]. With the continuous improvement of China's financial level and the promotion of the government's green finance policy, social capital has begun to flow into industries related to clean energy and environmental protection. Suitable financing models attract more long-term investments in green energy infrastructures necessary to achieve energy targets [52]. The renewable energy industry needs financial support in the early stages [53,54]. Enterprises have been encouraged to focus on energy management and environmental protection and to invest more in green technology innovation, thereby boosting energy usage efficiency and minimizing energy pollution emissions [55–57]. The digital economy can alleviate energy poverty by promoting financial development. Accordingly, Hypothesis 3 is proposed:

Hypothesis 3 (H3). *The digital economy can have an indirect mitigating effect on energy poverty through financial development.*

3.4. Spatial Clustering of Energy Poverty

Energy development constraints and energy capacity consumption are important causes of energy poverty, and energy poverty may be spatially clustered due to differences in energy policies and production technology levels in different regions. On the one hand, the development and utilization of energy is constrained by policy, transportation, and environmental factors. In the energy-rich western regions, due to the influence of national ecological protection measures and long transportation distances enterprises are often reluctant to develop energy due to legal regulations and transportation costs, resulting in energy poverty problems persisting [58]. Neighboring areas are subject to a certain degree of environmental control as well, which in turn affects their energy development and utilization. Accordingly, there may be clustering characteristics in energy poverty. On the other hand, the level of production technology determines the level of energy production capacity. High energy-producing regions need a continuous inflow of energy from other regions, while energy outflow regions have decreasing capacity due to the gradual depletion of energy, thus making energy capacity have spatial agglomeration characteristics [59]. In addition, China's traditional coal-based energy transportation system has disadvantages. China's coal consumption accounts for about 70% of primary energy, and the limited transportation capacity constrains energy transportation, especially coal transportation, an important factor that in turn hinders China's economic development [60]. Overall, this raises the cost of energy transportation and reduces its efficiency, which further fosters the clustering of energy poverty. Accordingly, Hypothesis 4 is proposed:

Hypothesis 4 (H4). *Energy poverty is characterized by a certain degree of spatial clustering.*

The mechanism analysis is manifested in Figure 1.

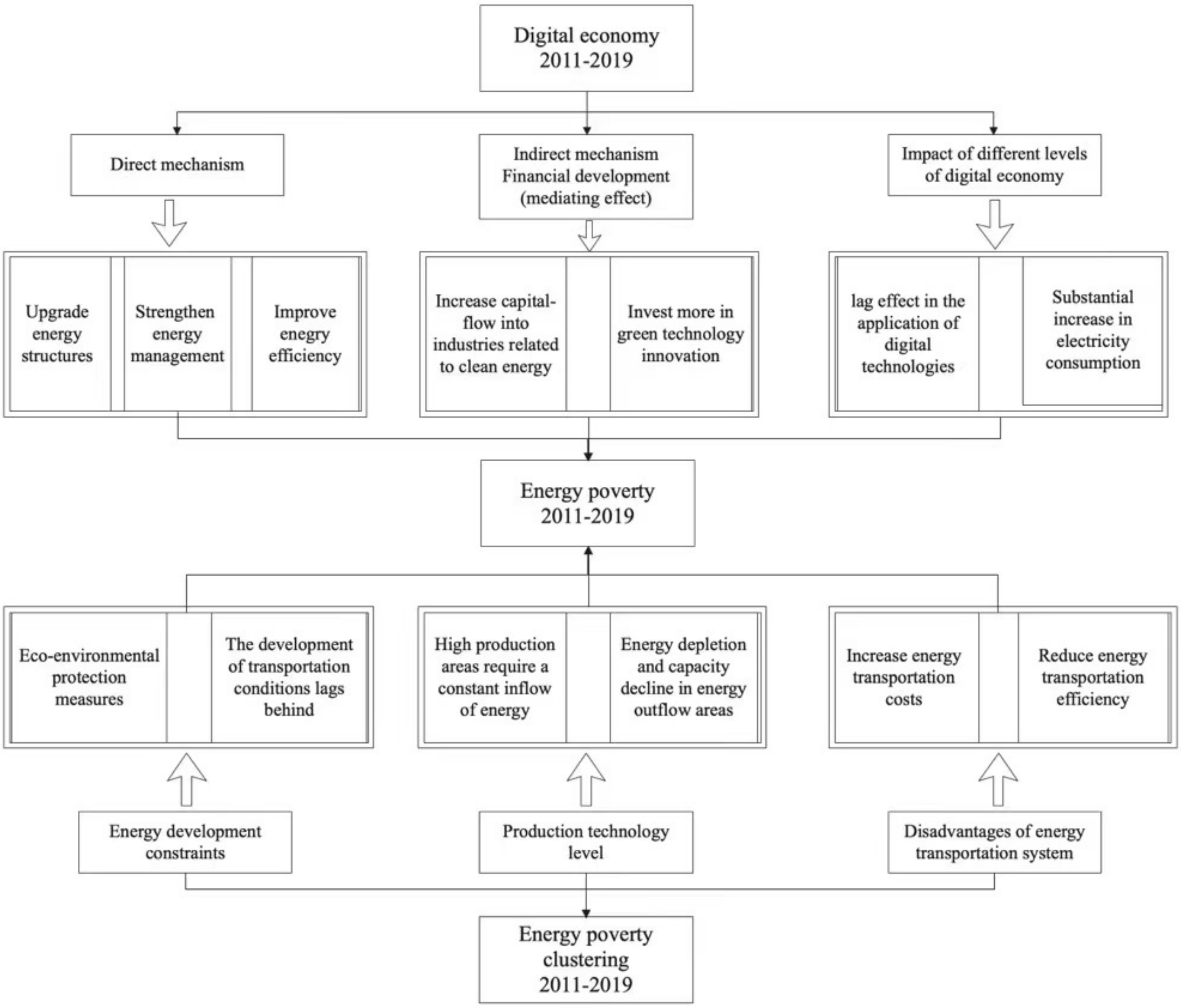

Figure 1. Mechanism analysis diagram.

4. Research Design and Description of Variables

4.1. Model Settings

In order to examine the direct impact of the digital economy on energy poverty, the benchmark regression model was set as follows:

$$REPI_{it} = \beta_0 + \beta_1 DE_{it} + \sum Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

where the explained variable $REPI_{it}$ is the energy poverty index of province i in year t; the core explanatory variable DE_{it} represents the digital economy index of province i in year t; the regression coefficient β_1 denotes the impact of the digital economy on regional energy poverty; and $\sum Control_{it}$ represents the control variables that may affect energy poverty of province i in year t. Individual effects, fixed effects, and random error terms are denoted by μ_i, ν_t, and ε_{it}, respectively.

In order to further examine the potential indirect impact of the digital economy on energy poverty, the mediating variable of financial development was introduced to construct a mediating effect model:

$$FD_{it} = \alpha_0 + \alpha_1 DE_{it} + \sum Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

$$REPI_{it} = \delta_0 + \delta_1 DE_{it} + \eta_1 FD_{it} + \sum Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

where FD_{it} represents the financial development level of province i in year t; δ_1 denotes the direct impact of the digital economy on energy poverty; and $\alpha_1 \times \eta_1$ represents the mediation effect of financial development in the process of the digital economy affecting energy poverty.

4.2. Variable Description

4.2.1. Explained Variable: Energy Poverty Index (*REPI*)

Based on the definition of energy poverty used in the United Nations Development Programme (2000), this paper develops a comprehensive energy poverty indicator system with reference to related studies [4,61]. In this study, four aspects (energy service availability, cleanliness of daily energy use, energy management efficiency, and living energy level) were chosen to depict the energy poverty situation in China and measure the regional energy poverty level in China from 2011 to 2019; the comprehensive evaluation index system is shown in Table 1.

Table 1. Comprehensive evaluation index system of energy poverty.

	First-level indicator	Secondary indicator	Third-level indicator
Energy poverty index	Availability of energy services	Energy for life	Electricity consumption per capita
			Natural gas consumption per capita
		Energy supply capacity	Urban gas penetration rate
			Urban per capita natural gas supply
	Cleanliness for daily use	Low-carbon energy structure	Proportion of clean energy power generation
		Energy structure modernization	Proportion of traditional biomass energy in total energy consumption
	Energy management efficiency	Energy management infrastructure	Rural energy management extension institutions per million per capita
		Energy investment	Rural energy investment per capita
			State-owned economy electricity, steam, hot water production, and supply per capita fixed assets
	Living energy level	Living energy cost	Per capita electricity and fuel expenditure in cities and towns as a share of total income
			Per capita domestic fuel expenditure in rural areas as a percentage of total income
		Energy consumption equipment	Number of range hoods owned by every 100 households in rural areas
			Number of energy-saving coal stoves per 100 people in rural areas
			Rural household biogas digester usage ratio
		Health effects of energy pollution	Domestic sulfur dioxide emissions per capita
			Domestic soot emissions per capita

Considering the different magnitudes, scales, and attributes of the 16 third-level indicators involved in the indicator system, the original data were processed without dimensions. The specific standardization formula was as follows:

If the evaluation index is a cost index, then

$$X_{ij}' = \frac{maxX_{ij} - X_{ij}}{maxX_{ij} - minX_{ij}} \tag{4}$$

If the evaluation index is a benefit index, then

$$X_{ij}{}' = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}} \tag{5}$$

The j index of region i is converted into a proper dimensionless index, $maxX_{ij}$, representing the maximum value of the j index; $minX_{ij}$ represents the minimum value of the X_{ij} index; and i represents the initial data of the j indicator of region i. After the data were standardized, the benefit-type and cost-type indicators in this study were unified into cost-type indicators. That is, the smaller the regional energy poverty comprehensive index, the less severe the corresponding regional energy poverty.

To analyze the evolutionary trend of energy poverty in different regions, a kernel density estimation method was used and Stata 16 was adopted to assess the complexity of energy poverty in certain years (Figure 2).

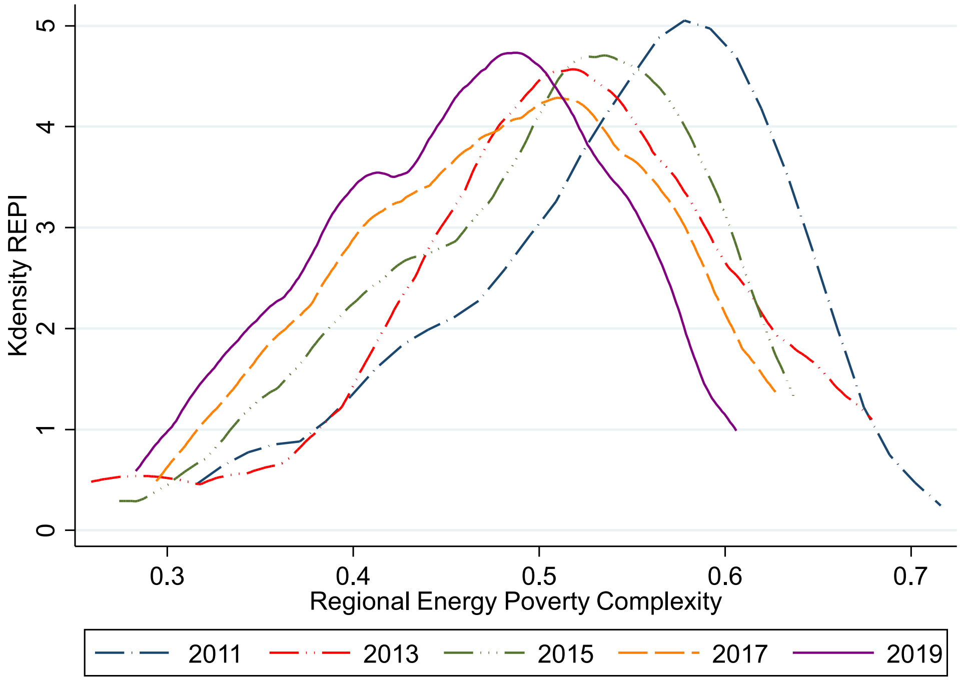

Figure 2. Kernel density trends of energy poverty complexity.

During the study period, the kernel density curve gradually changes to the left, suggesting a downward trend in regional energy poverty throughout China. In addition, the short tail on the left side of the curve shrinks to the right, as does the tail on the right, suggesting that the density of the distribution at both ends is gradually diminishing. The overall peak of the curve has a downward tendency, and the width rises each year, indicating that although the energy poverty situation in each province has improved, the disparity between provinces is growing.

Due to the severe disparity in resource endowment across different regions in China, there are considerable regional differences in energy poverty. As depicted in Figure 3, the national level of energy poverty decreased from 2011 to 2019, revealing that the degree of energy poverty in China was mitigated during the study period. The level of energy poverty in the eastern, central, and western areas exhibits a clear declining trend from a regional perspective. The central region shows the worst energy poverty situation, followed by the western and eastern regions.

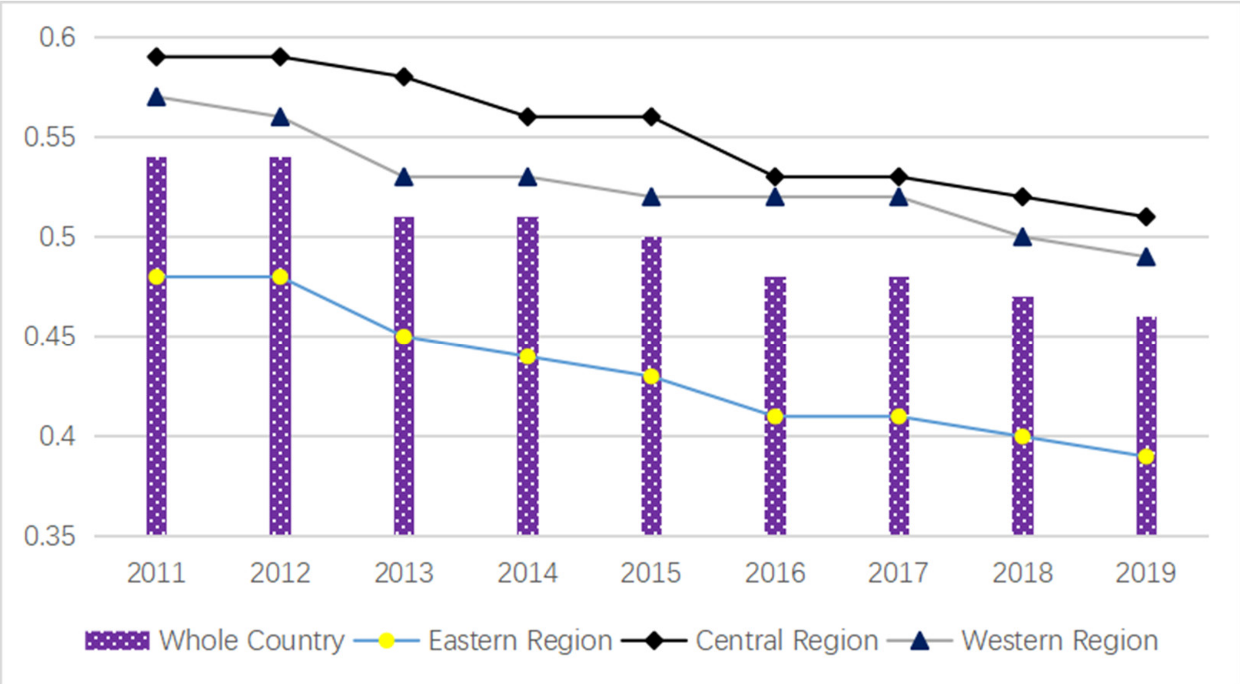

Figure 3. Trend of energy poverty in the country and regions.

At the same time, in order to further examine whether energy poverty is spatially autocorrelated, this study used the following formula to calculate the Moran index of energy poverty:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{6}$$

where n is the number of spatial individuals; n = 30; S^2 is the overall variance of the sample; y_i denotes the energy poverty of region I; $\overline{y}$ is the mean value of regional energy poverty; and w_{ij} is the spatial weight element. This study constructed the spatial weight matrix using adjacent indicators. If region i is adjacent to region j, the space weight value $w_{ij} = 1$; otherwise $w_{ij} = 0$.

4.2.2. Core Explanatory Variables: Digital Economy (*DE*)

The digital economy is classified into three tiers: level of digital infrastructure development, level of digital industry development, and level of digital technology innovation, referring to related research [8,13,22,62]. Infrastructure is a prerequisite for the implementation and growth of the digital economy, and its progress is directly related to the size and quality of the digital economy. This study assessed the construction level of digital infrastructure through three secondary indicators: total amount of telecommunication services, number of mobile phone users, and internet penetration rate. The development level of the digital industry represents the growth of the digital economy in a region. We considered output, employment, and business income as secondary indicators. In addition, the integration of the digital economy is particularly common in the service industry, which may more properly represent the development level of the digital industry. This study adopted the internet-related service industry in the indicator system based on the quantifiability of indicators. The comprehensive index of the digital economy development level was calculated by the extreme value method and the entropy value method, as shown in Table 2.

Table 2. Comprehensive evaluation index system of the digital economy.

Comprehensive Indicators	First-Level Indicator	Secondary Indicator	Nature
Digital economy	Digital infrastructure construction level	Total telecom business	+
		Number of mobile phone users	+
		Internet penetration rate	+
	Digital industry development level	Output of information service industry	+
		Employment in information services industry	+
		Information service business income	+
	Digital technology innovation and scientific research level	R&D spending	+
		Total number of talents, with bachelor's degree or above	+

In addition, Stata 16 was adopted for kernel density estimation and to analyze the complexity of the digital economy; Figure 4 illustrates the dynamic trends. During the research period, the kernel density curve of the digital economy showed a trend of shifting to the right, indicating that the development level of China's digital economy is rising annually. The left tail of the curve shifts to the left, while the right tail has remained relatively unchanged, indicating that regions with a high level of digital economic development continue to have significant advantages. In addition, the peak of the curve steadily decreases and the width expands, indicating that while the provinces' digital economy growth is generally improving, regional disparities are growing.

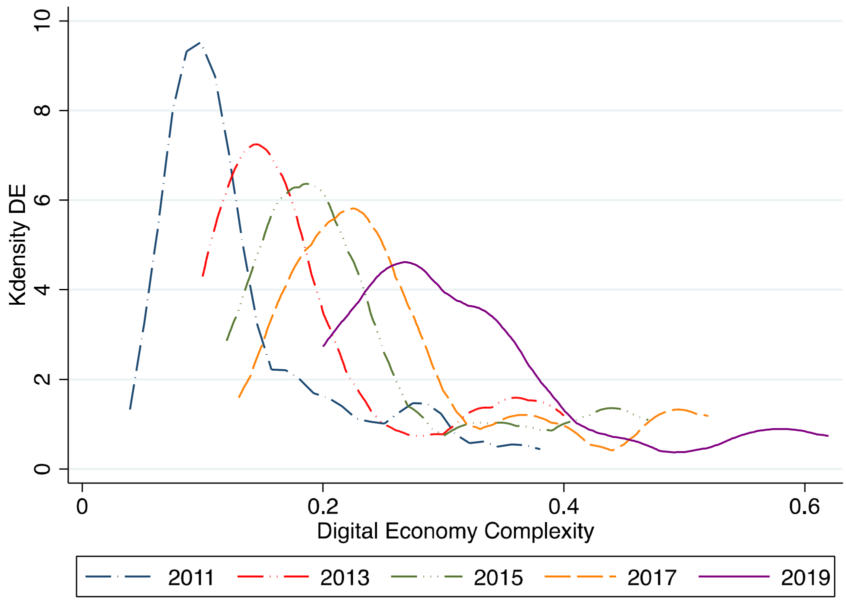

Figure 4. Kernel density trends of digital economy complexity.

There are obvious regional heterogeneities in the development of digital economies. As indicated in Figure 5, the national level of the digital economy is on an accelerating upward trend, which is mostly attributable to China's increasing emphasis on the digital economy and the rapid innovation and deployment of digital technology. Regionally, the digital economy is expanding, with the eastern, central, and western regions experiencing increases of 105%, 170%, and 189%, respectively. Despite the fact that the eastern region's digital economy is developing at a slower rate than the central and western regions, it has significant advantages and is in the lead. The central region is growing the fastest, while the digital economy in the west needs to be improved.

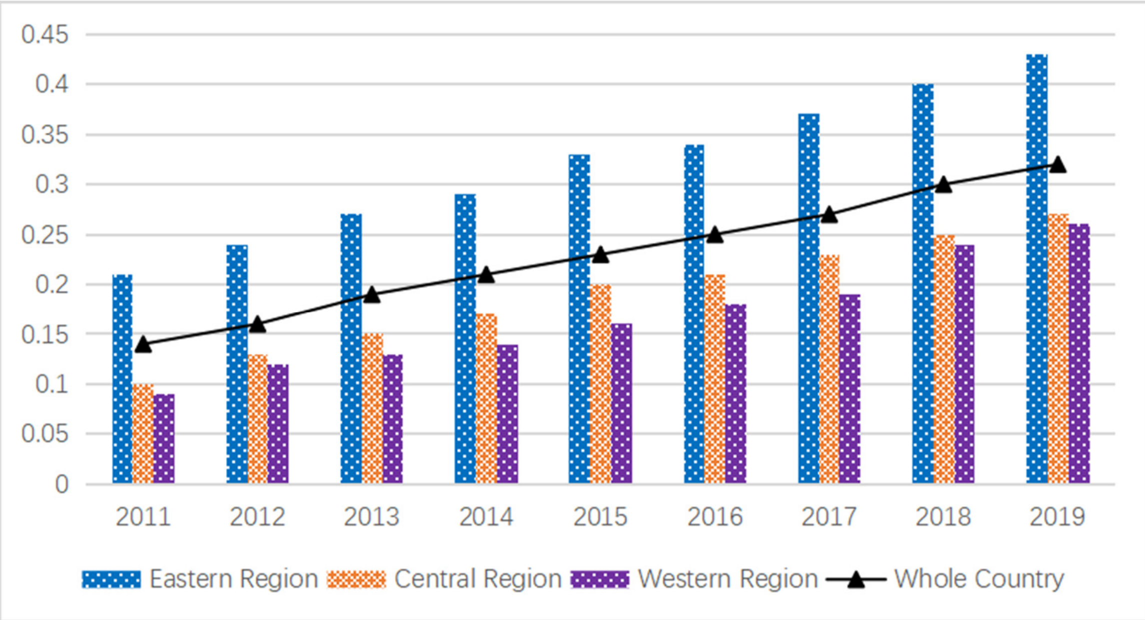

Figure 5. Trend in the development of digital economy in the country and regions.

4.2.3. Mediating Variable: Financial Development (*FD*)

This research examined the mechanism of the indirect effects of the digital economy on energy poverty by employing financial development as a mediating variable. Based on Li et al.'s (2019) [63] research on financial development, this study measured the level of financial development from three perspectives: financial scale, financial structure, and financial efficiency. Financial scale was evaluated by financial capital share and financial penetration. The financial structure was assessed by bank concentration and the proportion of REPIdent savings. Bank efficiency was measured as the ratio of financial deposits to loans and the savings-to-investment conversion rate. The entropy method was used to calculate the comprehensive index of financial development level by weighting the following six secondary variables.

4.2.4. Control Variables

To avoid estimation errors induced by other elements in the empirical model, certain variables that may affect energy poverty were chosen as control variables.

(1) Economic development level (*GDP*). Energy is the fundamental driver of economic growth, and economic expansion eventually results in changes to the energy structure. This study measured economic development by calculating the natural logarithm of GDP per capita.

(2) Permanent REPIdent population (*RP*). Population is a crucial factor for analyzing energy demand and energy supply as well as a determinant of energy poverty [13], and this study used the natural logarithm of the local population to measure it.

(3) Industrial structure upgrading (*ISU*). Optimizing the production structure and raising the share of tertiary industry can improve energy efficiency [13]. This research calculated the value-added ratio between tertiary and secondary industry to evaluate the level of industrial structure upgrading.

(4) Physical capital stock (*PCS*). To an extent, the stock of physical capital represents the operating scale and resource investment intensity of an enterprise. With the enterprise's continuous expansion of its production scale, its energy consumption increases, which may have an effect on energy poverty. This study took 2005 as the base period, used a GDP deflator to uniformly convert the capital stock data into 2005 prices, and then took the logarithm to measure PCS.

(5) Urbanization rate (*UR*). Rapid urbanization growth eventually results in changes in the energy supply and demand structure [64]. In this paper, the urbanization rate is represented by the ratio of urban to regional population.

(6) Environmental regulation (*ER*). As a result of the government's efforts to improve environmental governance and regulation, energy pollution emissions can be reduced by a certain amount, which has an effect on energy poverty [14,65]. Referring to the study of He (2018) [66], this research employs the principal component analysis approach to generate a complete index of three types of environmental regulation, namely, the command, market, and participatory types.

4.2.5. Data Sources

Considering the availability and accuracy of data, this study took 30 provinces (cities and regions) across the country as the research objects (excluding Tibet, Hong Kong, Macau, and Taiwan); the research period was 2011–2019. The data in this study mainly come from the *China Statistical Yearbook*, *China Agricultural Statistics*, *China Population and Employment Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Urban Statistical Yearbook*, *China Energy Statistical Yearbook*, and the statistical yearbooks of various provinces. The missing values in these data were estimated using the fitting method. Table 3 shows the descriptive statistics of the main variables.

Table 3. Descriptive statistics of variables.

Variable	N	Mean	S.D.	Min.	Max.
Energy poverty (*REPI*)	270	0.4995	0.0873	0.2590	0.6870
Digital economy (*DE*)	270	0.2308	0.1132	0.0600	0.6200
Financial development (*FD*)	270	0.3246	0.0954	0.1780	0.6620
Economic development (*GDP*)	270	10.8098	0.4340	9.7058	12.0090
Permanent REPIdent (*RP*)	270	8.2042	0.7349	6.3424	9.3519
Industrial structure (*ISU*)	270	2.3591	0.1221	2.1660	2.8320
Capital stock (*PCS*)	270	10.5505	0.7605	8.2451	12.0693
Urbanization rate (*UR*)	270	0.5763	0.1217	0.3500	0.8960
Environmental regulation (*ER*)	270	0.4764	0.3504	0.0004	2.4100

5. Analysis of Empirical Results

5.1. Benchmark Regression

To examine the linear relationship between the digital economy and energy poverty, this study first regressed the digital economy and energy poverty separately using Stata 16, then added control variables, dummy variables, and lagged terms. Table 4 displays the specific results of the regression.

From the perspective of the core explanatory variables, without adding any control variables, the digital economy's regression coefficient in Column 1 of Table 4 is −0.4802 and passes the significance test at the 1% level. This suggests that the digital economy significantly mitigates energy poverty. Adding the control variables in Column 2, the regression coefficient of the digital economy remains significantly negative at the 1% significance level, indicating that the digital economy continues to have a significant alleviating effect on energy poverty after controlling for other influencing factors, verifying Hypothesis 1. The widespread use of digital technologies can optimize energy consumption structures and improve energy management efficiency. Specifically, digital technologies can optimize energy allocation and encourage the development and utilization of new energy sources. Moreover, digitalization can reduce energy poverty by monitoring energy usage in real time and making appropriate adjustments and controls based on intelligent management systems.

Table 4. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)	(5)
	REPI	*REPI*	*REPI*	*REPI*	*REPI*
DE	−0.4802 ***	−0.3019 ***			−0.2754 ***
	(−4.61)	(−3.98)			(−3.23)
L.DE				−0.3871 ***	
				(−4.40)	
H_DE×*DE*			−0.2855 ***		
			(−3.59)		
L_DE×*DE*			−0.2263 **		
			(−2.48)		
GDP		−0.0985 ***	−0.0990 ***	−0.0903 **	−0.0920 ***
		(−2.99)	(−3.11)	(−2.36)	(−2.97)
RP		−0.0821	−0.0368	−0.1477	−0.1286
		(−0.52)	(−0.21)	(−0.90)	(−0.75)
ISU		−0.0126	−0.0094	0.0128	−0.0238
		(−0.21)	(−0.17)	(0.21)	(−0.42)
PCS		0.1302 **	0.1292 **	0.1251 **	0.1567 ***
		(2.57)	(2.58)	(1.99)	(2.84)
UR					−0.3317
					(−1.36)
ER					0.0108
					(0.67)
Constant	0.6061 ***	1.0070	0.6370	1.4524	1.2477
	(39.84)	(0.79)	(0.45)	(1.25)	(0.93)
Time effect	YES	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES	YES
N	270	270	270	240	270
AR^2	0.567	0.618	0.624	0.604	0.627

Note: The corresponding standard errors are in brackets; ** and *** represent significant at the 5% and 1% levels, respectively.

In terms of control variables, only the coefficients of GDP and physical capital stock are statistically significant. The regional GDP coefficient is significantly negative at the 1% level, suggesting that the higher the regional economic level, the less serious the situation of energy poverty. Economic growth ultimately both leads to an increase in energy demand and play a critical role in reducing energy poverty. Considering that China is currently transitioning from high-speed economic growth to high-quality economic development, green economic development is receiving increasing attention. In order to lower energy consumption costs and thereby minimize regional energy poverty, local governments should make more efforts to enhance energy infrastructure and invest more in new energy development. Physical capital stock is positively related to energy poverty at a significant level of 5%, indicating that it exacerbates regional energy poverty. This could be because an increase in capital stock inevitably leads to growth in the enterprise's production and operational scale, and therefore increases its energy demand. As more energy is extracted and used, the total amount of energy in the region falls, and the situation of energy poverty worsens.

From the perspective of the different development levels of the digital economy, it is necessary to further explore the specific conditions required in order for the digital economy to exert its effect on energy poverty. Referring to the experience of Li and Bai (2020) [67], two dummy variables were defined, high digital economy level (*H_DE*) and low digital economy level (*L_DE*), with the median of the digital economy as the boundary. For *H_DE*, when the digital economy level is greater than the median, the value is 1, otherwise it is 0; for *L_DE*, when the digital economy level is lower than the median, the value is 1, otherwise it is 0. The dummy variables *H_DE* and *L_DE* were each multiplied with the digital economy index, followed by regression analysis. The results of the regression are displayed in Column 3 of Table 4. The coefficient of the high digital economy level multiplied by the digital economy index is significantly negative at the 1% level of significance, while the coefficient of the low digital economy level multiplied by the digital economy index is significant at the 5% level of significance. This suggests that the digital economy at a high development level has a more significant effect on energy poverty alleviation, verifying Hypothesis 2. In the early stages of development of the digital economy, the alleviation effect of a low digital economy level on energy poverty is not obvious due to the backward construction of digital infrastructure, insufficient application coverage of digital information technology, and low energy utilization efficiency. However, along with the optimization and upgrading of digital technology and wide application, energy utilization efficiency has been improved, the scale of new energy development and utilization has been expanded, and environmental pollution has been further curbed, making the alleviation effect of a high digital economy level on energy poverty significant.

5.2. Mediation Effect

Based on the above analysis, the development of the digital economy can increase the scale and efficiency of financial services, reduce energy consumption efficiency and pollution emissions, and thus eliminate energy poverty. Therefore, this study applied Stata 16 and the mediation model to assess the mediating effects of financial development at the overall and regional levels.

5.2.1. Full-Sample Regression Results

To improve the accuracy of the conclusion, this study estimated the following equations with time and individual double fixed effects. The full-sample regression results of the mediation impact of financial development are shown in Table 5. Column 1 shows that the digital economy significantly decreases energy poverty, satisfying the first requirement of the mediation effect. At the 1% significance level, in Column 2 the coefficient of the digital economy is significantly negative, suggesting that it promotes financial development. The financial industry has undergone digital changes in products and services with the development of the digital economy, promoting cost reductions, efficiency improvements, service optimization, and model innovation, resulting in a sustainable increase in the financial industry's development speed and scale. The digital economy and the mediating variable (financial development) were regressed together with energy poverty, shown in Column 3. The coefficient of the digital economy is significantly negative at the 5% level of significance and the coefficient of financial development is significantly negative at the 1% level with −0.2140 and −0.2763, respectively. The coefficient of the digital economy is reduced compared to the total effect of −0.3019 in Column 1. It is clear that financial development has a partial mediating impact in the process of the digital economy eliminating energy poverty, accounting for 29.14% of the total effect. This demonstrates that the advancement of the digital economy might help to alleviate energy poverty by enhancing financial development. The bootstrap approach was used with 1000 sampling times for estimation in order to systematically examine the significance, and the 95% confidence interval did not contain 0, revealing that financial development's intermediary effect is significant and verifying Hypothesis 3. As the main body regulating the allocation of funds in various sectors, financial institutions certainly influence the allocation of funds for environmental management and energy inputs, which in turn has an impact on energy poverty. The combination of digitalization and traditional financial institutions brings about the improvement of financial service efficiency, scale, and structure, which further deepens the role of financial development in alleviating energy poverty. Thus, financial development plays a mediating effect in the process of energy poverty alleviation by the digital economy.

Table 5. Test of mediating effect of digital economy on energy poverty with full sample.

Variable	(1)	(2)	(3)
	REPI	*FD*	*REPI*
DE	−0.3019 ***	−0.3184 ***	−0.2140 **
	(−3.98)	(4.00)	(−2.41)
FD			−0.2763 ***
			(−3.08)
Control	YES	YES	YES
Constant	1.0070	3.6149 ***	2.0058
	(0.79)	(3.95)	(1.47)
Time effect	YES	YES	YES
Individual effect	YES	YES	YES
N	270	270	270
R^2	0.618	0.833	0.641
	Mediation effect	95% confidence interval	Is it significant
FD	−0.0458	[−0.0788,	YES
	(0.02)	−0.0187]	

Note: The corresponding standard errors are in brackets; ** and *** represent significant at the 5% and 1% levels, respectively.

5.2.2. Regional Regression Results

This study continued to conduct an empirical analysis of the mediating role of the eastern, central, and western regions, and the regression results are shown in Table 6. The preceding heterogeneity analysis covers the total influence of the digital economy on energy poverty in the eastern, central, and western areas. The results in Column 1 of Table 6 show that the development of the digital economy plays a significant role in enhancing the degree of financial development in the eastern region. The results in Column 2 show that both financial development and the digital economy have significant mitigating effects on energy poverty, while the coefficient of the digital economy and its significance decreases compared to Column 1, suggesting that digital economy may have an effect on energy poverty through the mediating variable of financial development. Similarly, there may be a mediating effect in the western region. In contrast, for the central region, the level of digital economic development shown in Column 3 does not have a significant effect on financial development, and there may not be a mediating effect.

Table 6. Test of the mediating effect of digital economy on energy poverty by region.

	East		Central		West	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
	FD	*REPI*	*FD*	*REPI*	*FD*	*REPI*
DE	0.5497 ***	−0.2474 **	0.2126	−0.5963 ***	0.2164 **	−0.2167
	(5.84)	(−2.37)	(0.68)	(−5.39)	(2.46)	(−1.27)
FD		−0.2271 **		−0.1703		−0.4245 *
		(−2.62)		(−1.08)		(−2.05)
Control	YES	YES	YES	YES	YES	YES
Constant	1.7451	0.3598	−2.6014	6.4829 *	3.9021 *	8.0872 **
	(1.74)	(0.17)	(−0.53)	(2.11)	(−1.94)	(3.10)
Time effect	YES	YES	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES	YES	YES
N	99	99	72	72	99	99
AR^2	0.796	0.744	0.895	0.743	0.895	0.631

Note: The corresponding standard errors are in brackets; *, ** and *** represent significant at the 10%, 5% and 1% levels, respectively.

According to the results of the bootstrap test in Table 7, the 95% confidence interval in the eastern region does not contain 0 and the mediation effect is significant, while the 95% confidence interval in the central and western regions contains 0, which means that the mediation effect is not significant in these two regions.

Table 7. Bootstrap test of the intermediary effect of subregional financial development.

FD	Mediation Effect	95% Confidence Interval	Significant
Eastern regions	−0.0510 (0.02)	[−0.0991, −0.0136]	YES
Central regions	0.0007 (0.13)	[−0.2339, 0.2717]	NO
Western regions	−0.0958 (0.05)	[−0.2165, 0.0006]	NO

5.3. Robustness Test

5.3.1. Adding Control Variables

The robustness of the regression results was tested in Stata 16 by gradually increasing the control variables; the results are shown in Table 4. Column 1 contains no control variables, Column 2 contains four control variables, and Column 5 contains two additional control variables. At the 1% significance level, the coefficients of the digital economy are always negative. The regression results are robust. In addition, with the introduction of control variables, the value of AR^2 rises, which verifies the estimation's robustness to an extent.

5.3.2. Endogenous Test

There is endogeneity caused by the two-way causality between the digital economy and energy poverty; the development of the digital economy can significantly alleviate energy poverty, while the intensification of energy poverty can constrain the development of the digital economy. To avoid biased estimation caused by this endogeneity in the empirical process, considering that the development of the digital economy has a lagged effect on energy poverty and the energy poverty in the current period does not affect the development of the digital economy in the previous period, the lagged period of the digital economy (*L.DE*) is chosen. The regression results of the one lagged period are shown in Column 4 of Table 4. The coefficient of the lagged term of the digital economy (*L.DE*) is −0.3871, significant at the 1% level, which suggests that the development of the digital economy does have a significant mitigating effect on energy poverty after the endogeneity is solved. This proves the reliability of the regression results.

6. Further Analysis

6.1. Spatial Autocorrelation Analysis of Energy Poverty

Spatial autocorrelation is the potential spatial dependency of variables in a geographical distribution affected by spatial interactions and spatial diffusion [68]. Energy poverty in one region may increase the energy demand for nearby regions, which in turn affects the energy supply of neighboring regions. To meet the needs of economic development among different regions, there is an energy trade-off in neighboring regions due to the disparities in regional resource endowments. In addition, the emission intensity of energy pollution has an impact on the environmental quality of neighboring areas and on their energy poverty. Spatial autocorrelation analysis of energy poverty could provide a beneficial reference for policy-making through revealing the characteristics of the spatial distribution of energy poverty in China.

In order to explore whether a single region has an impact on energy poverty in neighboring regions, global and local autocorrelation tests for energy poverty were conducted in 30 provinces (cities and regions) across China using Stata 16.

6.1.1. Global Spatial Autocorrelation Analysis

The Moran's index of energy poverty in 30 provinces of China from 2011 to 2019 was calculated based on Formula (6), and the results are presented in Table 8. The Moran's index of energy poverty was positive in all 30 provinces, and the value of the Moran's index fell from 2011 to 2013, suggesting that the positive spatial correlation of China's energy poverty was gradually reduced in these years. After 2014, the Moran's index has continuously increased in fluctuation, and its significance has risen year after year. The Moran's indexes for each year from 2016–2019 all passed the 1% significance test, which suggests that China's energy poverty has gained obvious spatial characteristics.

Table 8. Overall Moran's I of energy poverty in China from 2011 to 2019.

Year	Moran's I	E(I)	Sd(I)	z	*p*-Value
2011	0.193 **	−0.034	0.123	1.857	0.032
2012	0.105	−0.034	0.120	1.160	0.123
2013	0.088	−0.034	0.121	1.014	0.155
2014	0.154 *	−0.034	0.121	1.564	0.059
2015	0.222 **	−0.034	0.122	2.100	0.018
2016	0.361 ***	−0.034	0.123	3.213	0.001
2017	0.276 ***	−0.034	0.124	2.500	0.006
2018	0.282 ***	−0.034	0.124	2.561	0.005
2019	0.263 ***	−0.034	0.123	2.414	0.008

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

6.1.2. Local Spatial Autocorrelation Analysis

Different from the global Moran's index, the local Moran's index describes the spatial agglomeration of a spatial unit and its surrounding areas. The Moran's I scatterplot can more intuitively reflect the local spatial autocorrelation state of energy poverty. In this study, the Moran's I scatterplot divides the energy poverty status of 30 Chinese provinces into four types: (1) the first quadrant is the H–H type, indicating areas with higher energy poverty that are adjacent to areas with higher energy poverty; (2) the second quadrant is the L–H type, indicating areas in which the energy poverty level is relatively high and the energy poverty level in the surrounding areas is relatively low; (3) the L–L type in the third quadrant illustrates areas with lower energy poverty levels which are adjacent to other areas with low energy poverty levels; and (4) the H–L type in the fourth quadrant means places with higher energy poverty that are next to those with lower energy poverty. Furthermore, types H–H and L–L imply positive spatial correlations, whereas types H–L and L–H suggest negative spatial correlations.

Figures 6–10 depict the spatial distribution of energy poverty agglomerations in 30 provinces in 2011, 2013, 2015, 2017, and 2019.

From the Moran scatterplots (Figures 6–10), it can be seen that the majority of provinces in 2011, 2013, 2015, 2017, and 2019 were clustered in the first and third quadrants, suggesting that China's energy poverty predominantly displays high–high and low–low patterns, respectively. Although some provinces experienced fluctuations during the research period, the overall situation remained relatively stable. Among them, regions with high energy poverty and high agglomeration for a long time mainly include central regions (represented by Hubei, Hunan, and Henan), southwest regions (represented by Sichuan, Chongqing, and Yunnan), and northeast regions (represented by Jilin and Heilongjiang), verifying Hypothesis 4. The regions with low energy poverty and low agglomeration are Beijing, Guangdong, and the Yangtze River Delta regions. Therefore, from 2011 to 2019, energy poverty in China was mainly present in the central, southwest, and northeast regions; therefore, H4 is valid. Due to the different resource endowments, energy policies, and production technology levels in different regions, there are different degrees of differences in the development and utilization of energy and production capacity levels, etc. Moreover, the degree of development of transportation conditions determines the cost of energy transmission, meaning that there may be a spatial agglomeration of energy poverty.

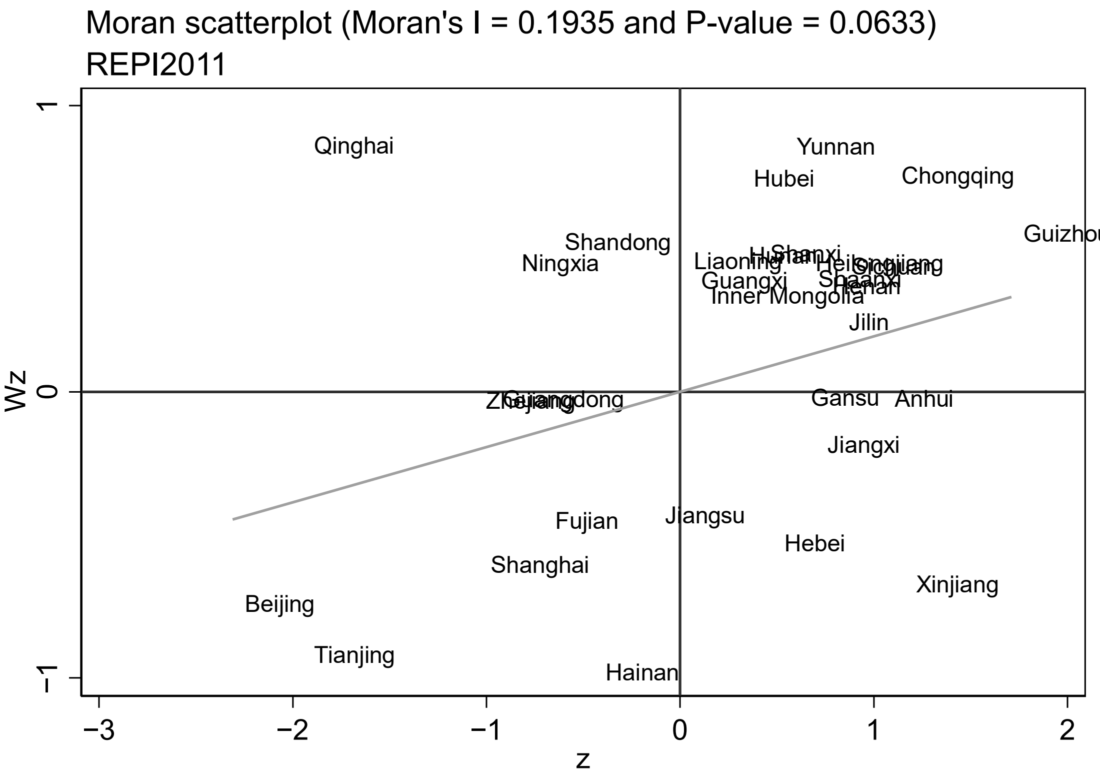

Figure 6. Moran scatterplot for 2011.

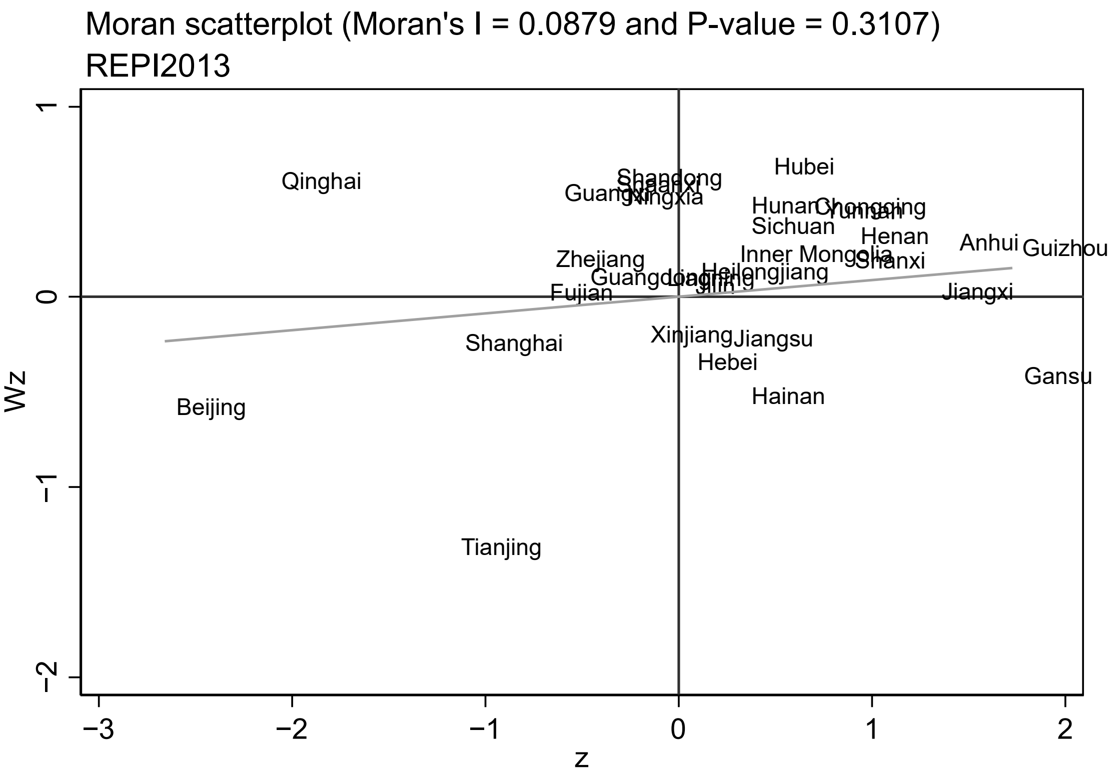

Figure 7. Moran scatterplot for 2013.

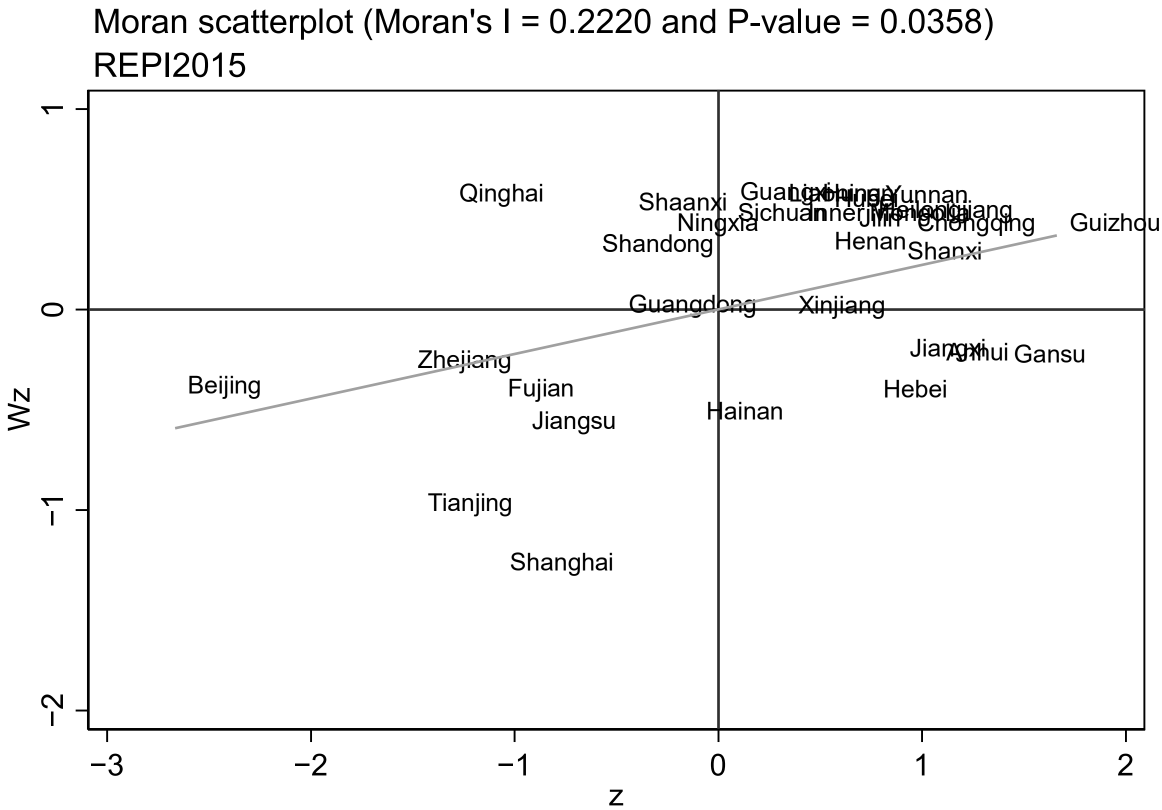

Figure 8. Moran scatterplot for 2015.

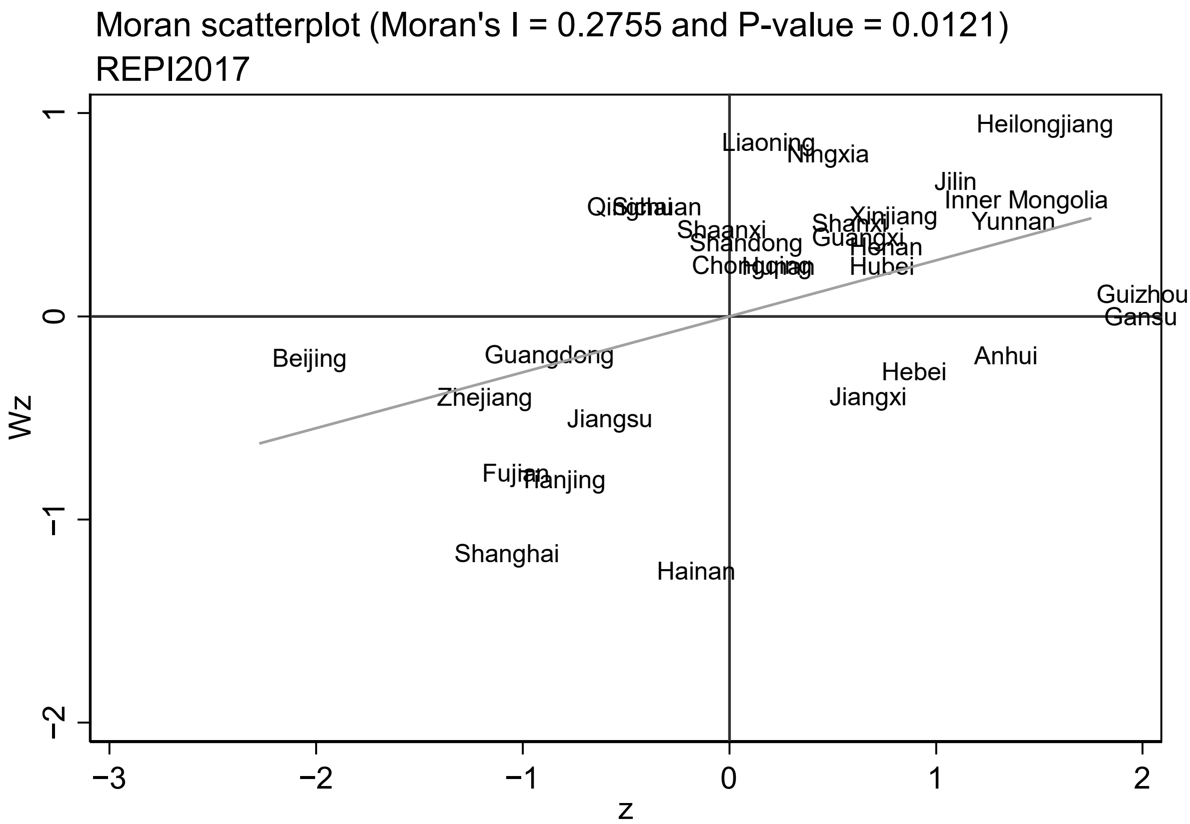

Figure 9. Moran scatterplot for 2017.

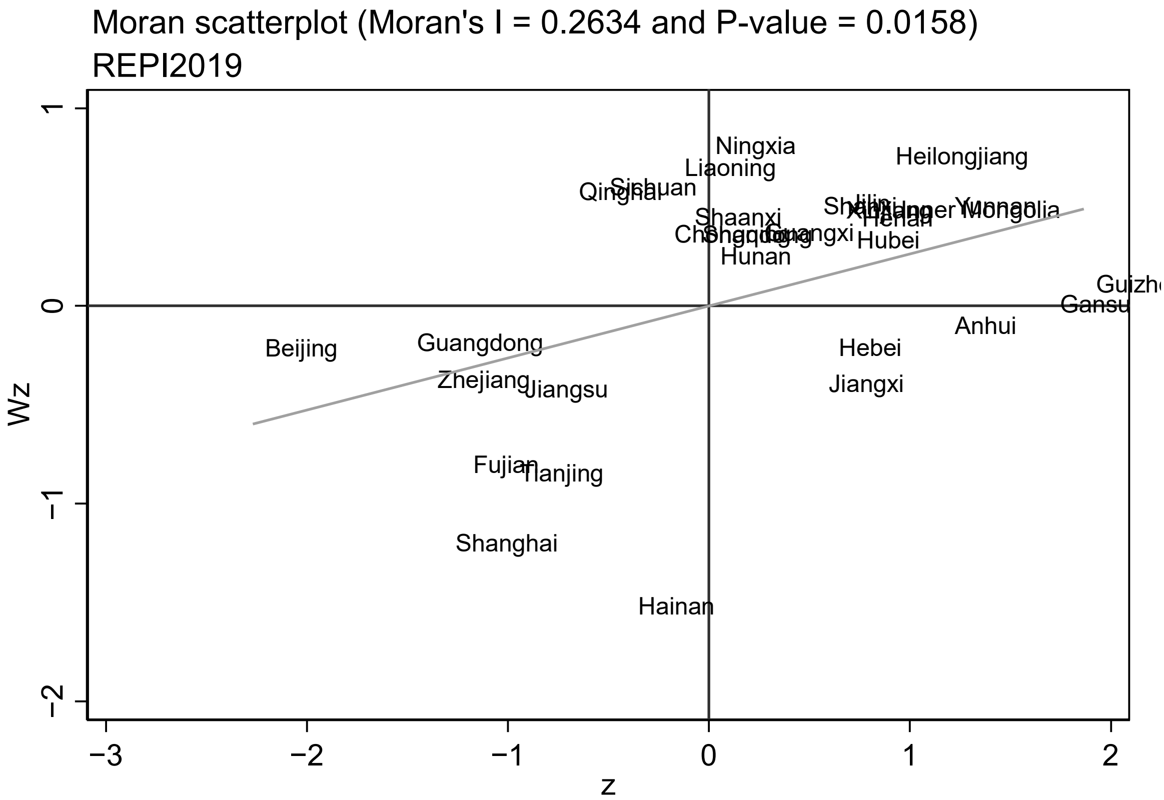

Figure 10. Moran scatterplot for 2019.

6.2. Heterogeneity Analysis

The above research reveals that the digital economy has the potential to relieve overall energy poverty. Furthermore, in light of the significant discrepancies between the development of the digital economy and the severity of energy poverty in different regions, we can ask whether the effects of the digital economy on energy poverty vary across regions. The present study proceeded to estimate regional heterogeneity using Stata 16, and the estimated results are shown in Table 9.

Table 9. Heterogeneity analysis of eastern, central, and western regions.

Variable	**East**	**Central**	**West**
	(1)	**(2)**	**(3)**
DE	−0.3722 **	−0.6325 ***	−0.3086
	(−4.14)	(−4.06)	(−1.67)
Control variable	YES	YES	YES
Constant	−0.0365	6.9260 *	6.4307 *
	(−0.02)	(1.96)	(2.22)
Time effect	YES	YES	YES
Individual effect	YES	YES	YES
N	99	72	99
R^2	0.723	0.736	0.607

Note: The corresponding standard errors are in brackets; *, **, and *** represent significant at the 10%, 5%, and 1% levels, respectively.

As shown in Table 9, the coefficients of the level of digital economic development (*DE*) are significantly negative at the 5% level in the eastern regions, significantly negative at the 1% level in the central regions, and insignificant in the western regions. In addition, the absolute value of the coefficient is larger in central China than in the eastern and western areas, suggesting that there are significant regional differences in the digital economy's effect on energy poverty. Specifically, even though the development of the digital economy in the eastern region has reached a high level, its energy poverty level has remained relatively low since 2016, leaving a small potential space for the digital economy to alleviate energy poverty in a short period of time. Thus, the digital economy has had a limited impact on reducing energy poverty. While the central regions have optimized their energy structure and improved their energy management efficiency with the increasing expansion of their digital industry in recent years, they face the most acute energy deprivation. The space and possibilities for alleviating energy poverty are vast. Consequently, the digital economy's mitigation effect on energy poverty is more significant. In the western regions, the development basis of the digital economy is relatively weak, making it more difficult to combat energy poverty. In addition, because the western regions consist mostly of natural reserves, the broad application of digital technology and the exploitation of energy are undertaken with considerable caution, limiting the digital economy's alleviating effect on energy poverty.

7. Conclusions and Recommendations

In the context of the increasingly prominent global energy crisis, in-depth analysis of the role of the digital economy in alleviating energy poverty can drive the energy industry to digital transformation, promote the development and utilization of new energy sources, and help reduce environmental pollution. This is of great significance for improving energy efficiency and accelerating financial development to alleviate energy poverty and promote the high-quality development of China's economy. Based on panel data from 30 provinces (municipalities and districts) in China from 2011 to 2019, this study first analyzed the regional differences between the level of development of the digital economy and the degree of energy poverty, then empirically examined the linear impact and nonlinear characteristics of the digital economy on energy poverty. On this basis, an intermediary effect model was established to explore whether financial development plays a role in the process of influencing energy poverty in the digital economy. Finally, the spatial agglomeration characteristics of energy poverty and the regional heterogeneity of the weakening effect were clarified. The results show that: (1) the digital economy has a significant mitigation effect on energy poverty with obvious regional heterogeneity, with the mitigation effect in the central region being significantly higher than in the central and western regions, and the mitigation effect is more obvious at higher levels of digital economic development; (2) financial development is one of the mechanisms by which the digital economy alleviates energy poverty; and (3) the energy poverty of the whole country has obvious spatial agglomeration characteristics.

The following policy implications are proposed according to our theoretical analysis and empirical findings.

(1) Accelerate the process of digital construction and boost the energy revolution. Continuously improve the construction of digital infrastructure, promote technological innovation in energy transportation, integrate power transmission into the comprehensive energy transportation system, and reduce the total cost of social energy transportation. Continue to increase capital investment in digital technology innovation, promote the development and utilization of new energy, guide the transformation of the energy consumption structure to clean and green, and inject new impetus into alleviating energy poverty. Promote the optimization and upgrading of digital intelligent management systems, build an energy consumption monitoring and control service system, reduce human resource costs, and improve energy management and utilization efficiency.

(2) Continue to promote the development of digital finance and green finance. Accelerate the financial application of digital technology, improve the coverage and availability of financial services, reduce financial risks and financing costs, and provide strong financial support for the development of the energy industry. Improve financial support policies for the green transformation of energy, innovate green financial service products, guide the flow of funds to clean energy technology development and ecological environmental pro-

tection industries, improve energy utilization efficiency, reduce energy pollution emissions, and more effectively alleviate energy poverty.

(3) Implement differentiated energy management strategies. According to the spatial agglomeration characteristics of energy poverty, differentiated energy management targets according to local conditions can be formulated for different regions. For agglomeration areas with a high degree of energy poverty, it is necessary to enhance the monitoring and research and development functions of digital technology, combine financial service policies, and increase investment in energy management and energy structure optimization. At the same time, it is necessary to make full use of the spatial spillover effect of low–low energy poverty agglomeration areas, gradually expand the radiation range of low–low energy poor areas, and promote China's overall goal of eliminating energy poverty. This study theoretically analyzes and quantitatively evaluates the impact of the digital economy on energy poverty, and provides a beneficial reference for further alleviating energy poverty via the digital economy and optimizing related policies. However, this paper only examined financial development as one of the indirect mechanisms by which the digital economy alleviates energy poverty, and did not cover other possible intermediary effects. In addition, with the rapid development and application of new energy sources, the definition of energy poverty needs to be further improved. Therefore, in future research, the continuous tracking of other indirect mechanisms of the digital economy that affect energy poverty and the definition and measurement of energy poverty are important directions worthy of in-depth study.

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