

## Article

# The Promotion of Sustainable Energy: How Does Digital Economy Attention Enhance Green Total Factor Energy Efficiency?

Xinyi Tu <sup>1</sup>, Tingting Li <sup>2</sup>, Linlin Ding <sup>2</sup>, Heguang Liu <sup>2,\*</sup> and Jinkai Li <sup>3,\*</sup>

<sup>1</sup> Faculty of Management & Economics, Kunming University of Science and Technology, Kunming 650500, China; ttuxinyii@163.com

<sup>2</sup> Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Science, Beijing 100081, China; 18237671019@163.com (T.L.); dinglinlin@caas.cn (L.D.)

<sup>3</sup> College of Economics and Management, China Agricultural University, Beijing 100083, China

\* Correspondence: liuheguang@caas.cn (H.L.); jinkai.li@cau.edu.cn (J.L.)

**Abstract:** As global digital transformation accelerates alongside the “dual carbon” goal, understanding how the digital economy can drive the green transformation of traditional energy systems is critical to overcoming resource and environmental constraints. This study examines the impact of digital economy attention on Green Total Factor Energy Efficiency (GTREE) using panel data from 275 Chinese prefecture-level cities between 2011 and 2022. Three main findings emerged. First, an increase in attention to the digital economy significantly enhances GTREE, serving as a key driver of improved energy efficiency. Specifically, a one-standard-deviation increase in attention raises GTREE by 0.276 standard deviations. Second, this effect operates through two pathways: (1) digital technology advancements, such as higher internet penetration; (2) human capital accumulation, reflected in a greater college student ratio; and (3) green innovation, measured by a rise in green patents. Third, regional heterogeneity is evident, with stronger positive effects in eastern and coastal cities, while high-carbon-intensity regions exhibit a suppressed impact. These results underscore the importance of public engagement in digitalization to optimize energy systems. Policymakers should adopt region-specific strategies, such as boosting digital infrastructure in low-carbon areas and supporting structural reforms in high-carbon regions. This study expands our understanding of the digital economy’s role in enhancing energy efficiency and offers policy guidance for the green energy transition.



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**Keywords:** digital economy attention; green total factor energy efficiency; mechanism test; heterogeneity analysis

## 1. Introduction

Amidst escalating global energy demands and a deepening climate crisis, the unsustainability of traditional energy systems has transitioned from a theoretical concern to an urgent global challenge. Data from the International Energy Agency (IEA) reveals that fossil fuels still dominate over 80% of the world’s energy consumption, with their associated carbon emissions and environmental degradation not only destabilizing ecosystems but also directly hindering progress toward the United Nations Sustainable Development Goals (SDGs), particularly in clean energy adoption and climate action [1]. Without significant structural shifts in the energy mix, global temperature increases are projected to exceed the critical thresholds outlined in the Paris Agreement, amplifying risks of extreme weather events and socioeconomic disparities. In this context, the digital economy has emerged as a transformative force for addressing energy sustainability. Empirical evidence

highlights its multifaceted contributions: intelligent algorithms optimize energy distribution efficiency [2], blockchain ensures verifiable carbon footprint monitoring [3], and data-driven analytics catalyze industrial energy efficiency advancements [4]. Collectively, These innovations position GTFEE, a globally recognized standard for reconciling energy security and ecological conservation, as an achievable goal through technology integration.

Nevertheless, the global energy transition continues to confront critical bottlenecks: first, persistent fossil fuel path dependency has hindered the widespread adoption of clean energy technologies [5]; second, inefficient energy utilization patterns amplify environmental governance costs [6]; third, disparities in regional resource endowments exacerbate inequities in transition outcomes [7,8]. Although extant literature has examined the nexus between the digital economy and energy efficiency, scholarly efforts predominantly center on macroeconomic outcomes of technological proliferation or rigid policy architectures [9,10], thereby neglecting the catalytic role of dynamic socio-cognitive mechanisms, especially digital economy attention, in guiding energy system transformation. While prior studies validate digitalization, human capital, and green innovation as pivotal enablers of energy efficiency and acknowledge the digital economy's facilitative role in these domains [11–14], how societal prioritization of the digital economy mobilizes these drivers through cognitive-institutional pathways remains uncharted territory. Three unresolved questions encapsulate this research gap: (1) Direct Impact: Does heightened attention to the digital economy exhibit a direct positive effect on GTFEE, and what is the magnitude of this relationship? (2) Mediation Pathways: Are the adoption of digital technologies, the accumulation of human capital, green-foundation innovations, and the regulation of the environment central mediators in transmitting this effect? (3) How do regional resource endowments moderate the effectiveness of digital economy concerns in enhancing GTFEE?

To address these research questions, this study utilizes panel data from 275 prefecture-level cities in China (2011–2022) and employs a two-way fixed-effect model to conduct benchmark regressions, mechanism tests, moderating effect analyses, and heterogeneity assessments. The results demonstrate that heightened societal attention to the digital economy exerts a statistically significant positive impact on GTFEE. This effect is further amplified through three synergistic pathways: advancing informatization infrastructure, fostering human capital accumulation, and strengthening green innovation capacity, collectively driving sustainable urban energy transitions.

By constructing a novel analytical framework linking digital economy attention and GTFEE, this research advances the theoretical framework for green sustainable development. Furthermore, by dissecting the causal pathways and magnitude of digital economy attention's influence on GTFEE, the study enriches empirical scholarship on green economic transformation and provides targeted policy countermeasures to optimize resource allocation. These findings hold dual significance: theoretically, they deepen the understanding of cognitive drivers in energy system transitions; practically, they offer actionable insights for enhancing energy efficiency and addressing global energy-climate challenges.

## 2. Literature Review and Research Hypothesis

This study establishes a theoretical framework centered on the “digital economy attention–GTFEE” interaction through four systematic steps. First, we delineate the conceptual boundaries and methodological foundations of digital economy attention, examining its dynamic evolution shaped by technological advancements, policy interventions, and regional economic disparities. Second, we define the core dimensions and measurement paradigms of GTFEE, identifying its multidimensional drivers: technological innovation, industrial structural, and environmental regulation. Third, we synthesize existing literature to unveil the mediating mechanisms through which digital economy attention may

enhance GTFEE, including innovation diffusion, policy responsiveness, and societal behavioral adaptation. Finally, we bridge theoretical gaps by formulating testable hypotheses, thereby establishing a foundation for empirical validation of their bidirectional interplay.

### *2.1. Measurement and Influencing Factors of Digital Economy Attention*

As a metric reflecting public perceptions of technological change potential, the measurement of digital economy attention primarily utilizes media data frequency analysis and search engine analytics [15–17]. The driving mechanisms operate through dual pathways: first, technological innovation breakthroughs such as artificial intelligence and blockchain amplify public engagement by elevating expectations for practical applications [18,19]; second, policy regulation: government interventions shape societal attention through resource allocation and regulatory frameworks [20]. Notably, regional developmental disparities create heterogeneous drivers: developed regions emphasize digital-industry convergence to sustain competitive edges, whereas developing regions prioritize visibility through digital catch-up strategies [21].

### *2.2. Measurement of GTFEE and Relative Influencing Factors*

Green Total Factor Energy Efficiency (GTTEE) provides an integrated perspective for measuring the sustainability of energy systems by incorporating environmental constraints, such as pollutant emissions, into traditional energy efficiency assessment systems. In terms of measurement methods, academics mainly use two types of frameworks. One is non-parametric models, such as Data Envelopment Analysis (DEA), which calculates relative efficiency values by comparing input factors (e.g., labor, capital, energy) with output outcomes (e.g., GDP, industrial pollutants) in different regions [22,23]. (Data Envelopment Analysis (DEA) is a nonparametric method for assessing the relative efficiency of multiple-input multiple-output systems. It treats the decision units to be evaluated as black boxes and determines the efficiency of each decision unit by comparing its production frontier surface. Commonly used models include the CCR model and BCC model. The advantage of DEA is that it is able to deal with multiple input and output indicators at the same time, without the need to pre-set the weights, and avoids the interference of human factors on the results. In addition, it is able to provide specific improvement suggestions for ineffective decision-making units). The second is parametric tools, such as the Malmquist–Luenberger index, which tracks trends in efficiency over time by dynamically incorporating environmental constraints, such as carbon emissions, and which is particularly suited to assessing a region’s ability to adapt to sustainable development goals in the face of policy and technological change [24]. (The SBM–Malmquist–Luenberger index is a dynamic efficiency analysis tool based on non-parametric DEA. By combining the SBM model (a non-radial efficiency measure dealing with relaxation variables) with the directional distance function, it can effectively deal with multi-input multi-output systems containing undesirable outputs (such as pollutant emissions). The index can not only measure the dynamic change in total factor productivity (TFP) but also be further decomposed into technical efficiency change and technological progress index, which is suitable for efficiency assessment in complex scenarios such as environmental regulation and green economy. Its advantage is that it overcomes the processing defects of traditional radial model for non-expected output and balances the weight of expected and non-expected output by introducing directional distance function. It is widely used in carbon emission efficiency, ecological efficiency and other fields, and is especially suitable for evaluating the dynamic performance of regions or industries under the sustainable development goals). GTTEE enhancement relies on three major synergistic mechanisms. First, green technology innovations such as breakthroughs in photovoltaic technology or wind energy systems can

directly reduce the dependence on fossil fuels for energy production and their environmental costs [25]. Second, the transformation of the industrial structure is crucial: the transition from high energy-consuming industries to high value-added, low-emission industries has significantly reduced the energy intensity per unit of output [26]. Finally, stringent environmental regulations force firms to adopt energy-efficient technologies and optimize production processes, creating a virtuous cycle of “constraints–innovation–efficiency” [27]. The interplay of these pathways constructs a systematic, multi-layered propulsion network for GTFEE advancement.

### 2.3. *The Relationship Between Digital Economy Attention and GTFEE*

While prior research has rarely incorporated digital economy attention and GTFEE into a unified analytical framework, critical interaction mechanisms between the two have begun to surface. Heightened public attention to the digital economy acts as a catalyst for technological innovation, mobilizing firms and research institutions to integrate digital tools, and increased R&D investments accelerate the application of these hybrid technologies in energy management and decarbonized production processes, directly enhancing GTFEE through operational efficiency gains [2]. Concurrently, fluctuations in societal attention serve as market signals, steering capital and policy support toward digitally transformative industries while diminishing the economic viability of energy-intensive sectors. This structural reallocation reduces the dominance of high-pollution activities, indirectly elevating GTFEE by reshaping industrial energy consumption patterns [28].

Furthermore, rising digital economy attention exerts pressure on policymakers to innovate regulatory frameworks, prompting governments to implement dual-track measures such as green technology subsidies and stringent emission standards. These policies create a self-reinforcing cycle: they directly incentivize corporate green R&D while indirectly optimizing market dynamics through price signals, thereby establishing a causal chain where attention drives policy refinement, which in turn amplifies efficiency outcomes [29]. Collectively, these mechanisms illustrate how digital economy attention transcends passive awareness to actively orchestrate multidimensional pathways for GTFEE advancement.

### 2.4. *Research Hypothesis*

Driven by breakthroughs in digital technologies such as internet big data and artificial intelligence, the digital economy has emerged as a core engine of China’s economic growth [30]. Its essence lies in reshaping resource allocation models and innovation paradigms through digitalization, establishing one that prioritizes environmental sustainability. Specifically, digital technologies not only achieve productivity leaps at reduced environmental costs but also enable precise energy consumption control to mitigate pollution emissions [31]. In this context, heightened public and corporate attention to the digital economy has fostered a “green orientation” in technology adoption: enterprises increasingly explore digital solutions for energy management, advancing the synergistic enhancement of energy efficiency and GTFEE [32]. Concurrently, rising societal expectations compel firms to amplify investments in green technology R&D, creating a self-reinforcing cycle of “digital innovation → energy efficiency optimization → credibility enhancement”. Thus, this study proposes the following hypothesis:

**Hypothesis 1:** *Digital economy attention can directly promote the development of GTFEE.*

Heightened attention to the digital economy incentivizes governments and businesses to intensify investments in digital infrastructure, thereby elevating internet penetration rates. Enhanced connectivity facilitates the broader application of digital technologies across energy production, transmission, and consumption. For instance, IoT systems

enable the interconnection and real-time monitoring of energy equipment, empowering enterprises to track energy usage with precision, adjust energy strategies dynamically, and optimize utilization efficiency [33]. Concurrently, the emphasis on the digital economy attracts talent inflows into related sectors, enhancing human capital quality. High-caliber professionals offer intellectual support for green energy technology innovation and management refinement [34], fostering the development of advanced green energy utilization methods that elevate GTFEE [35]. Given this, this study proposes the following hypothesis:

**Hypothesis 2:** *Digital economy attention can indirectly promote the development of GTFEE through optimizing digital technology and talent.*

Heightened attention to the digital economy incentivizes companies and research institutions to allocate greater resources to green technology R&D, thereby driving an increase in green patent grants [36]. The innovations encapsulated in these patents, spanning technologies and processes, can be directly integrated into energy systems, enhancing energy utilization efficiency, mitigating environmental harm, and advancing GTFEE [37]. Concurrently, rising public focus on the digital economy pressures governments to prioritize environmental sustainability, prompting stricter regulations in areas such as wastewater management and municipal waste disposal standards [38]. To comply with these elevated regulatory demands, enterprises are compelled to adopt advanced production technologies and circular management models, improving resource recycling rates, reducing process-related energy consumption, and indirectly bolstering GTFEE (Figure 1).

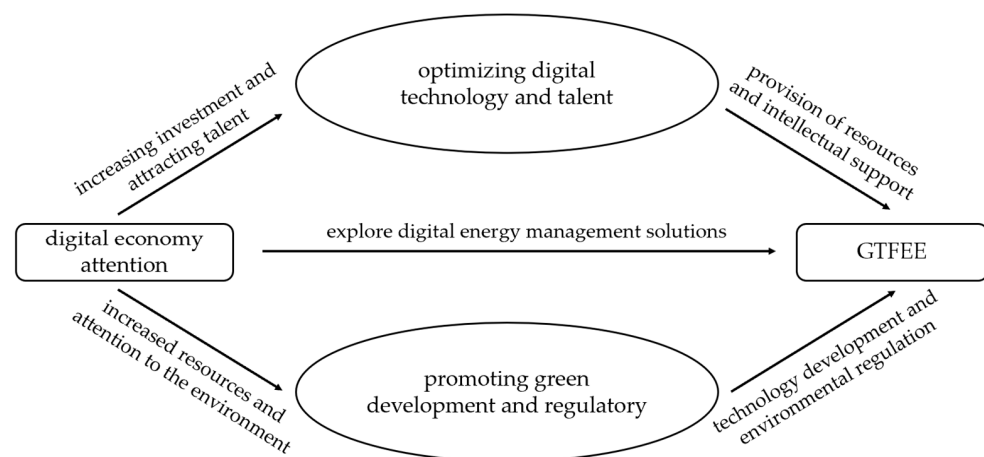


**Figure 1.** Conceptual framework diagram.

**Hypothesis 3:** *Digital economy attention can indirectly promote the development of GTFEE through promoting green development and regulatory advancements.*

### 3. Research Design

#### 3.1. Variable Selection

- (1) Explained variable: green total factor energy efficiency (GTFEE). Reference to existing studies [39], labor, capital, and energy were selected as inputs, gross domestic product (GDP) as consensual outputs, and industrial sulfur dioxide (SO<sub>2</sub>), industrial soot and dust (smoke) and industrial wastewater (effluents) emissions as non-consensual outputs, to the SBM–Malmquist–Luenberger index method to measure the GTFEE of each prefecture-level city.

- (2) Core explanatory variables: digital economy attention (Attention). In this study, we construct digital economy attention indicators at the prefecture-level city through the following process: first, we screen four core keywords: “digital economy”, “digitalization”, “digital technology”, “industrial digitization”, “digitalization”, “digital economy”, “digital technology”, and “industrialization”. First, the four core keywords covering the dimensions of the public’s awareness of digital economy policy, technology, and industrialization. Secondly, R language is used to crawl the average daily search volume data of the above keywords in Baidu index platform from 2011 to 2022 (Baidu index official website: <https://index.baidu.com/v2/index.html#/>, accessed on 31 December 2023), match the user’s IP address according to the administrative division code of prefecture-level cities, and then aggregate the data into panel data according to “prefecture-level city—year”. In order to integrate the information of multiple keywords and reduce the covariance, principal component analysis (PCA) was performed on the search volume of the four types of keywords, and the first principal component was extracted as the comprehensive search index. Finally, in order to eliminate the difference in scale and enhance comparability, the composite index is logarithmized and standardized for conversion [40]. This method captures the public’s dynamic interest in the digital economy through search heat, and the standardization process ensures the validity of cross-city comparisons.
- (3) Control variables: According to previous literature review, the empirical model also includes the following control variables: foreign direct investment (FDI), which may introduce high energy-consuming industries, inhibiting GTFEE [41,42]; industrial structure (IS), measured by the ratio of value added of the secondary industry to GDP—the proportion of high-tech manufacturing industries in the secondary industry has increased, and the energy intensity per unit of its output is lower than that of the traditional heavy industry, which is expected to have a positive impact on GTFEE [43]; economic development (lnPGDP), expressed as log GD per capita—the growth of GDP is usually accompanied by technological upgrading and strengthening of environmental protection awareness, driving GTFEE growth [44]; innovation capacity (IC), measured by the total number of patent applications for inventions, where an increase in green invention patents directly drives the optimization of energy efficiency, which is expected to positively increase GTFEE [44]; and the level of urbanization (UR), measured by utilizing the ratio of the urban population to the total population of each region, where population agglomeration promotes the scale effect and the diffusion of clean technologies, which is expected to positively affect GTFEE [45]. The size of government expenditure (GOV) is expressed by calculating the share of local fiscal expenditure in GDP and is expected to positively contribute to GTFEE, as fiscal investment may support green infrastructure and regulatory enhancement [43].

### 3.2. Econometric Model Setting

This study aims to investigate the impact of digital economy attention on GTFEE. Thus, GTFEE is used as the dependent variable and digital economy attention as the independent variable. City fixed effects can eliminate the interference of city traits that do not change over time on GTFEE; time fixed effects can absorb annual commonality shocks such as macroeconomic fluctuations and national policy adjustments; and bi-directional fixed effects constrain both the individual and temporal dimensions, which can more accurately identify the net effect of the digital economy’s attention compared to the mixed OLS or one-way fixed effects. Therefore, this paper refers to previous studies [45,46] and

constructs a two-way fixed effects framework as a benchmark regression using panel data for 275 Chinese cities from 2011 to 2022:

$$GTFEE_{it} = \partial_0 + \partial_1 \text{Attention}_{it} + \beta \text{Controls}_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where  $i$  indicates city,  $t$  denotes year,  $GTFEE_{it}$  is the green total factor energy efficiency,  $\text{Attention}_{it}$  denotes digital economy attention,  $\partial_0$  is the intercept term,  $\text{Controls}_{it}$  denotes control variable set,  $\mu_i$  denotes city fixed effects,  $\delta_t$  denotes time fixed effects, and  $\varepsilon_{it}$  is the random error term.

### 3.3. Data Sources and Descriptive Statistics

We use panel data for 275 prefecture-level cities in China from 2011 to 2022 as our sample. The data source includes the China Statistical Yearbook, China Energy Statistical Yearbook, the National Bureau of Statistics of China, and the official websites of local governments. There are a small number of missing time series for some of the variables. To maintain data continuity, missing values were supplemented using linear interpolation. The descriptive statistics are shown in Table 1.

**Table 1.** Descriptive statistics of variables.

| Variables | N    | Mean   | SD     | Min    | Max     |
|-----------|------|--------|--------|--------|---------|
| Attention | 3300 | 0.0598 | 0.119  | 0      | 1       |
| GTFEE     | 3300 | 0.345  | 0.140  | 0.103  | 1.177   |
| IC        | 3300 | 9053   | 21,291 | 19     | 320,813 |
| IS        | 3300 | 45.18  | 10.82  | 11.70  | 82.05   |
| lnPGDP    | 3300 | 10.78  | 0.565  | 8.773  | 13.06   |
| FDI       | 3300 | 758.7  | 1465   | 0.0200 | 14,004  |
| Gov       | 3300 | 0.201  | 0.102  | 0.0439 | 0.916   |
| UR        | 3300 | 0.493  | 0.202  | 0.110  | 2.456   |

## 4. Empirical Analysis

### 4.1. Benchmark Analysis

The benchmark regression results presented in Table 2 reveal several critical insights. The digital economy attention coefficient of 0.276 demonstrates substantial economic significance when contextualized against other model parameters. Specifically, a one-standard-deviation increase in digital economy attention corresponds to a 0.274 standard deviation improvement in GTFEE. In contrast, the coefficient on innovation capacity (IC) is significant, but the value is extremely small, well below the impact of Digital Economy Attention. The coefficient of Urbanization Rate (UR) is 0.156 but insignificant, suggesting that its impact on GTFEE is unclear. Meanwhile, the negative and insignificant coefficient on foreign direct investment (FDI) suggests that the impact of FDI on GTFEE is minimal and may reflect more of a structural issue in the allocation of foreign capital than an “efficiency issue”. This comparative analysis underscores digital economy attention as the dominant policy-relevant driver of GTFEE enhancement among the examined variables. This marginal effect validates the viability of the “attention-driven transformation” mechanism, implying that heightened public engagement with the digital economy assists cities in overcoming the “resource curse” accelerates GTFEE development, and positions it as a critical tool for advancing sustainable energy systems [47].

**Table 2.** Benchmark regression.

|                   | (1)                  | (2)                 |
|-------------------|----------------------|---------------------|
|                   | GTFEE                | GTFEE               |
| Attention         | 0.324 ***<br>(5.12)  | 0.276 ***<br>(3.69) |
| IC                |                      | 0.000 **<br>(2.13)  |
| IS                |                      | 0.001<br>(1.48)     |
| lnPGDP            |                      | 0.022<br>(1.20)     |
| FDI               |                      | −0.000<br>(−0.80)   |
| GOV               |                      | 0.024<br>(0.29)     |
| UR                |                      | 0.156<br>(1.51)     |
| Time fixed effect | YES                  | YES                 |
| City fixed effect | YES                  | YES                 |
| Constant          | 0.326 ***<br>(86.12) | −0.052<br>(−0.26)   |
| N                 | 3300                 | 3300                |
| R <sup>2</sup>    | 0.682                | 0.686               |

Notes: \*\*\*, \*\* denote significance at the 1%, 5% level, respectively. Standard errors are in brackets.

Increased public focus on the digital economy has catalyzed large-scale investments in information technology infrastructure, enhancing digital connectivity and enabling more efficient. Concurrently, digital technologies facilitate innovation in energy R&D and amplify the adoption of circular economy models, optimizing energy conversion efficiency and resource reuse. Rising environmental expectations have spurred governments to implement stringent policies, with IoT and blockchain technologies ensuring transparent enforcement. Enterprises, in response, are adopting advanced energy technologies and sustainable management frameworks to align with regulatory demands, reduce pollution, and maximize efficiency—a dynamic explored in-depth in Section 5.1 Mechanism analysis.

#### 4.2. Robustness Test

In order to improve the robustness of the previous regression results, this study conducted additional tests to check their validity. These tests included modifying the study period, indenting tails, breaking tails, substituting explanatory variables, substituting explanatory variables, and adding interaction terms for province and year, as shown in Table 3.

Column (1) considers the impact of COVID-19, with the sample period set to 2011–2020. Column (2) focuses on 2017–2022, a period during which the Chinese government explicitly prioritized the digital economy in its policy agenda. In 2017, the term “digital economy” was first introduced in the government work report, emphasizing the need to deepen “Internet+” initiatives and accelerate digital growth. Subsequent policies, including the National Development and Reform Commission’s Notice on Pilot Projects for Digital Economy Innovation (2018) and the Notice on Major Digital Economy Pilot Projects, further institutionalized its development post-2017. Columns (3) and (4) apply winsorization and trimming treatments to mitigate the influence of extreme values. Across all specifications, the coefficients of Attention remain significantly positive: Column (1) and Column (2)

demonstrate robust baseline results, while Columns (3) and (4) confirm the persistence of this relationship after addressing outliers.

**Table 3.** Robustness test.

|                              | (1)                  | (2)                  | (3)                 | (4)                 | (5)                   | (6)                  | (7)                 | (8)                 | (9)                 | (9)                 |
|------------------------------|----------------------|----------------------|---------------------|---------------------|-----------------------|----------------------|---------------------|---------------------|---------------------|---------------------|
|                              | GTFEE                | GTFEE                | GTFEE               | GTFEE               | lnEC                  | lnDust               | GTFEE               | GTFEE               | GTFEE               | GTFEE               |
| Attention                    | 0.224 **<br>(2.51)   | 0.326 ***<br>(4.52)  | 0.337 ***<br>(4.42) | 0.236 ***<br>(3.99) | −1.024 ***<br>(−7.57) | −0.262 **<br>(−2.30) |                     | 0.269 ***<br>(4.45) |                     | 0.110 ***<br>(2.88) |
| lnattention                  |                      |                      |                     |                     |                       |                      | 0.001 ***<br>(4.23) |                     |                     |                     |
| lag_attentions               |                      |                      |                     |                     |                       |                      |                     |                     | 0.273 ***<br>(3.11) |                     |
| Control variables            | YES                  | YES                  | YES                 | YES                 | YES                   | YES                  | YES                 | YES                 | YES                 | YES                 |
| Time fixed effect            | YES                  | YES                  | YES                 | YES                 | YES                   | YES                  | YES                 | YES                 | YES                 | YES                 |
| City fixed effect            | YES                  | YES                  | YES                 | YES                 | YES                   | YES                  | YES                 | YES                 | YES                 | YES                 |
| Province × Time fixed effect | NO                   | NO                   | NO                  | NO                  | NO                    | NO                   | NO                  | YES                 | NO                  | NO                  |
| Constant                     | 8.010 ***<br>(16.68) | 9.404 ***<br>(32.23) | 0.024<br>(0.13)     | −0.088<br>(−0.38)   | 8.010 ***<br>(16.68)  | 9.404 ***<br>(32.23) | 0.024<br>(0.13)     | −0.088<br>(−0.38)   | −0.109<br>(−0.51)   | 0.024<br>(0.12)     |
| N                            | 3113                 | 3113                 | 3103                | 3064                | 3113                  | 3113                 | 3103                | 3064                | 3025                | 3025                |
| R <sup>2</sup>               | 0.941                | 0.991                | 0.707               | 0.725               | 0.941                 | 0.991                | 0.707               | 0.725               | 0.723               | 0.815               |

Notes: \*\*\*, \*\* denote significance at the 1%, 5% level, respectively. Standard errors are in brackets.

Column (5) using city-level night lighting to invert city-level energy consumption [39,48]. Nighttime lighting data capture the brightness of urban lights through satellite imagery, the intensity of which is highly correlated with economic activity and energy consumption. It has been shown that light brightness can effectively invert regional energy usage. In this paper, we use ArcGIS to extract nighttime lighting data of prefecture-level cities and construct an energy consumption model, and the results show that digital economic attention significantly reduces energy consumption (coefficient −1.024), which indirectly verifies its enhancement effect on green energy efficiency. Column (6) employs the industrial soot release as a proxy variable for energy consumption. Industrial soot emissions are a direct product of fossil energy use, and their emissions can reflect the energy intensity of energy-consuming industries. This paper finds that digital economy attention significantly suppresses emissions (coefficient −0.262), suggesting that public attention promotes the application of cleaner technologies and the optimization of energy structure. Columns (5) and (6) show that digital economy concern has a significant negative inhibitory effect on energy consumption and industrial soot release. The two types of proxy variables validate the effect of digital economy concern in reducing resource waste and environmental pressure from the perspectives of macroscopic energy consumption and microscopic pollution emission, respectively, which enhances the robustness and logical self-consistency of the research findings.

Column (7) participates in the regression by making the logarithmic processing of the annual search index of the digital economy attention and the lnattention coefficient is zero. The lnattention coefficient is 0.001, and digital economy attention significantly increases GTFEE by 1% level; Column (8) adds the interaction term of province and year, and the Attention coefficient is still positive. To address reverse causality, Column (9) includes an explanatory variable (Attentions) lagged by one period [49]. The lagged term remains statistically significant, reinforcing the idea that digital economy attention precedes and drives energy efficiency improvements. Column (10) introduces the lagged dependent variable as a control variable, and the coefficient on digital economy attention remains significant at 1% even after accounting for historical trends in energy efficiency. The robustness test shows that the empirical results of this paper are stable and reliable.

#### 4.3. Mechanism Analysis

The preceding findings confirm that heightened attention to the digital economy exerts a positive influence on GTFEE. However, the precise transmission mechanisms underlying this relationship remain underexplored. Having established Hypothesis 1, this study now empirically examines Hypotheses 2 and 3, analyzing the mediating roles of digital technology adoption, human capital accumulation, green development policies, and regulatory frameworks.

To quantify these mechanisms, this paper measures informatization levels via city-wide internet penetration rates and evaluates human capital through the proportion of enrolled college students [50,51]. As shown in Column (1) of Table 4, the regression coefficient of digital economy attention on informatization is 14.828, signifying that public engagement directly accelerates digital infrastructure investment and subsequent technological diffusion. Column (2) reveals an even more pronounced effect on human capital, with a coefficient of 191.465, demonstrating that rising societal attention substantially expands the supply of skilled labor to support green technology implementation. Both coefficients are statistically significant at the 1% level, confirming the dual mechanisms of infrastructure upgrading and skill remodeling. Specifically, public pressure compels governments and firms to prioritize digital infrastructure expansion [52,53], enabling smart energy systems that optimize urban energy allocation [54]. Simultaneously, heightened societal expectations incentivize enterprises to invest in digital skills training and industry-academia collaboration, fostering talent pools specialized in green technologies [55]. This skilled workforce drives energy-consuming process automation and reduces energy intensity, thereby enhancing GTFEE. These results validate Hypothesis 2, demonstrating that digital economy attention elevates GTFEE through the synergistic pathways of “digital infrastructure expansion → human capital enhancement → energy efficiency optimization”.

**Table 4.** Mechanism test results.

|                   | (1)                  | (2)                   | (3)                   | (4)                  | (5)                   |
|-------------------|----------------------|-----------------------|-----------------------|----------------------|-----------------------|
|                   | Internetuser         | Human Capital         | Invention             | Sewage               | Harmless              |
| Attention         | 14.828 ***<br>(2.83) | 191.465 ***<br>(2.61) | 261.397 ***<br>(6.43) | 6.343<br>(1.00)      | 3.669<br>(0.67)       |
| Control variables | YES                  | YES                   | YES                   | YES                  | YES                   |
| Time fixed effect | YES                  | YES                   | YES                   | YES                  | YES                   |
| City fixed effect | YES                  | YES                   | YES                   | YES                  | YES                   |
| Constant          | 48.533 ***<br>(2.81) | 250.418 **<br>(1.99)  | 90.530<br>(1.08)      | 82.991 ***<br>(3.55) | 124.938 ***<br>(3.82) |
| N                 | 3113                 | 3113                  | 3113                  | 2948                 | 2948                  |
| R <sup>2</sup>    | 0.886                | 0.970                 | 0.907                 | 0.434                | 0.295                 |

Notes: \*\*\*, \*\* denote significance at the 1%, 5% level, respectively. Standard errors are in brackets.

In this paper, we measure innovation development by the number of green patents [56] and characterize the intensity of environmental regulation by the sewage and garbage disposal rates. As shown in Column (3) of Table 4, the regression coefficient of digital economy attention on green innovation is 261.397, indicating that heightened public scrutiny incentivizes green technology R&D, driving patent growth and providing technological foundations for energy efficiency optimization. Column (4) reports a coefficient of 6.343 for sewage treatment rates, suggesting a tentative link between digital economy attention and environmental governance investments, while Column (5) shows a coefficient of 3.669 for waste harmless disposal rates, hinting at potential efficiency gains in waste management. Critically, the green innovation coefficient in Column (3) is statistically significant at the 1% level, whereas Columns (4) and (5) lack statistical significance. These findings reveal that digital economy attention compels enterprises and research institutions to amplify green

innovation investments [57,58], with firms leveraging big data and AI to identify transformation needs and refine green technologies for reduced environmental footprints [59]. Concurrently, public expectations for digital–environmental synergy pressure governments to tighten environmental regulations [60]. Deploying IoT and blockchain technologies for real-time pollution monitoring, this dual dynamic forces enterprises to adopt energy-saving technologies and management upgrades, ultimately elevating GTFEE. While Hypothesis 3 is partially validated, the results underscore the critical role of public engagement in bridging digital and sustainable transitions.

#### 4.4. Heterogeneity Effect

Due to the differences in regional resource endowment and urban development levels, there is pronounced heterogeneity in public attention to digital economy and GTFEE among cities. In this regard, this paper further investigates the heterogeneity of the digital economy attention in the promotion of GTFEE based on the geographic location and economic level, as well as further study of prefecture-level cities in China.

##### 4.4.1. Carbon Intensity Heterogeneity

The carbon emission intensity was categorized into low carbon emission intensity cities, medium-low carbon emission intensity cities, medium-high carbon emission intensity cities, and high carbon emission intensity cities according to quartiles. Models (1)–(4) of Table 5 show that the effect of digital economy attention on GTFEE is significantly positive in low carbon emission intensity cities and medium-low carbon emission intensity cities. At the same time, the Attention coefficient is negative in medium-high carbon emission intensity cities and high carbon emission intensity cities, indicating that public attention to digital economy inhibits the development of GTFEE. The significantly positive effect of digital economy attention on GTFEE in low and medium-low carbon emission intensity cities is because enterprises' energy utilization and production patterns have less negative impact on the environment, and the pressure and cost of transformation are relatively low. Increased public attention to the digital economy encourages enterprises to carry out green innovation through digital technology. As the government strengthens environmental regulations, it is easier for enterprises to respond and increase energy saving and emission reduction, thus improving GTFEE [61,62].

**Table 5.** The heterogeneous impact by carbon intensity division.

|                   | Low                 | Medium-Low         | Medium-High       | High              |
|-------------------|---------------------|--------------------|-------------------|-------------------|
|                   | (1)                 | (2)                | (3)               | (4)               |
|                   | GTFEE               | GTFEE              | GTFEE             | GTFEE             |
| Attention         | 0.303 ***<br>(3.52) | 0.444 **<br>(2.42) | −0.022<br>(−0.15) | −0.152<br>(−0.53) |
| Control variables | YES                 | YES                | YES               | YES               |
| Time fixed effect | YES                 | YES                | YES               | YES               |
| City fixed effect | YES                 | YES                | YES               | YES               |
| Constant          | 0.389<br>(1.03)     | −0.006<br>(−0.02)  | 0.406<br>(1.16)   | −0.535<br>(−1.29) |
| N                 | 760                 | 771                | 772               | 745               |
| R <sup>2</sup>    | 0.818               | 0.749              | 0.765             | 0.689             |

Notes: \*\*\*, \*\* denote significance at the 1%, 5% level, respectively. Standard errors are in brackets.

##### 4.4.2. Economic Development Heterogeneity

As shown in Table 6, models (1)–(3) indicate that the impact of digital economy attention on GTFEE is more significant in eastern cities, and the impact of digital economy

attention on promoting GTFEE is more minor in central and western regions. The level of economic development and industrial structure of the eastern cities are more advanced, and the integration of digital technology and green development is closer, which helps to significantly improve GTFEE [63]. In contrast, the traditional industrial structure in the central and western regions limits the promotion of the digital economy. Second, technological innovation capacity and talent pool are more abundant in eastern cities, which are conducive to promoting GTFEE; at the same time, the central and western regions face the challenge of technology and talent shortage. Furthermore, infrastructure and policy support is better in eastern cities, which helps the digital economy promote green development, while there are gaps in central and western regions [64,65].

**Table 6.** The heterogeneous impact by geographical location.

|                   | East                | Center            | West               |
|-------------------|---------------------|-------------------|--------------------|
|                   | (1)                 | (2)               | (3)                |
|                   | GTFEE               | GTFEE             | GTFEE              |
| Attention         | 0.226 ***<br>(3.90) | 0.171 *<br>(1.79) | 0.190 **<br>(2.49) |
| Control variables | YES                 | YES               | YES                |
| Time fixed effect | YES                 | YES               | YES                |
| City fixed effect | YES                 | YES               | YES                |
| Constant          | −0.084<br>(−0.27)   | 0.101<br>(0.35)   | 0.075<br>(0.25)    |
| N                 | 996                 | 960               | 948                |
| R <sup>2</sup>    | 0.729               | 0.767             | 0.688              |

Notes: \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are in brackets.

As shown in Table 7, Columns (1) and (2) indicate that the influence of digital economy attention on GTFEE is more remarkable in coastal cities, mainly because coastal cities are economically developed [66]. Their industrial structure is dominated by high-tech and modern services, which makes them highly receptive to digital technology. They can easily combine digital technology with green development to enhance GTFEE.

**Table 7.** The heterogeneous impact of coastal and inland.

|                   | Coastal Cities     | Inland Cities       |
|-------------------|--------------------|---------------------|
|                   | (1)                | (2)                 |
|                   | GTFEE              | GTFEE               |
| Attention         | 0.297 **<br>(2.43) | 0.200 ***<br>(3.08) |
| Control variables | YES                | YES                 |
| Time fixed effect | YES                | YES                 |
| City fixed effect | YES                | YES                 |
| Constant          | −0.058<br>(−0.27)  | −0.294<br>(−1.18)   |
| N                 | 1233               | 1826                |
| R <sup>2</sup>    | 0.768              | 0.753               |

Notes: \*\*\*, \*\* denote significance at the 1%, 5% level, respectively. Standard errors are in brackets.

## 5. Conclusions and Implications

### 5.1. Conclusions

Based on the panel data of 275 prefecture-level cities in China from 2011 to 2022, this paper empirically analyzes the impact of digital economy attention on GTFEE by using a two-way fixed-effect model. The results show that for every one-standard-deviation

increase in digital economy attention, GTFEE increases by 0.274 standard deviations on average (Table 2), which highlights the catalytic role of public digital awareness in improving energy efficiency. The mechanism test shows that the attention of digital economy promotes the growth of GTFEE through digital technology and talent and green development. Regional heterogeneity analysis shows that the marginal effect is the largest in eastern coastal cities (coefficient 0.226) and low-carbon-intensity areas (coefficient 0.303), while the marginal effect of high-carbon-intensity cities is negative (coefficient  $-0.152$ ), indicating that the existence of “structure locking” effect hinders technology diffusion.

This study acknowledges two key limitations. First, the weak statistical significance of certain indicators in Hypothesis 3 may stem from sample size constraints or measurement biases, necessitating future refinement through expanded datasets or refined environmental regulation metrics. Second, data limitations exist: (1) Baidu Index metrics, while valuable, may reflect regional censorship or search engine algorithmic biases, limiting cross-platform generalizability; (2) keyword selection, though policy-aligned, risks excluding regional or emerging terms; and (3) nighttime lighting-derived energy data inadequately capture infrastructure disparities. Future research should integrate multi-platform data, apply NLP semantic analysis, and validate findings with multi-source datasets to enhance accuracy. Finally, the model may suffer from endogeneity problems such as omitted variables or bidirectional causation, although partial reverse causation has been controlled for through lagged variables, and further validation by an instrumental variables approach is needed in the future. These limitations highlight pathways for methodological advancements.

### 5.2. Implications

To start with, enhancing the attention of the digital economy. Governments should amplify public and corporate awareness of the digital economy through targeted campaigns, including professional forums, industry expos, and skill-building workshops. These initiatives foster a societal environment conducive to digital transformation while enhancing stakeholder capacity to leverage technological advancements. Concurrently, policymakers must align digital economy promotion with GTFEE goals by designing market-driven incentives and regulatory frameworks that encourage firms to adopt digital solutions for energy optimization, thereby harmonizing economic growth with ecological sustainability.

Furthermore, a two-pronged approach. To promote the development of the digital economy and enhance GTFEE, policymakers should focus on two main strategies. The first is to introduce incentive policies and set up funds to support the upgrading of network facilities, expanding Internet coverage, improving network performance and supporting informatization. At the same time, optimize educational resources, strengthen digital skills training, improve workforce quality, and support energy efficiency improvement. The second is to incentivize green innovation through tax incentives and financial subsidies, improve environmental regulations, promote digital technology in environmental management, and urge enterprises to save energy and reduce emissions, so as to achieve a win-win situation for both the environment and the economy.

Finally, developing policies according to local conditions. Low-carbon cities should leverage digital innovation hubs to accelerate AI-driven energy management and blockchain-enabled carbon auditing, streamlining green patent commercialization. In contrast, high-carbon cities require structural overhauls, deploying municipal big-data platforms to monitor energy-intensive industries and implementing progressive carbon taxation to phase out obsolete practices. Complementing this, regional digital transformation centers can support SMEs with technical training and computational resources, enabling gradual transitions to cleaner production. By combining technology intensification in low-carbon regions with structural substitution in high-carbon zones, this spatially

differentiated approach avoids one-size-fits-all pitfalls and maximizes energy efficiency gains across diverse urban contexts.

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