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Digital Economic Transformation and Green Energy Efficiency in China: Technology Diffusion and Institutional Conditions

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ABSTRACT

Against the backdrop of China's carbon-neutrality strategies and its trade relations with economies participating in the Regional Comprehensive Economic Partnership (RCEP), the potential of digitalisation to support a less energy-intensive economy has attracted growing policy and academic attention. Existing research remains limited in two respects. First, the mechanisms through which digital economic transformation is associated with green energy efficiency remain insufficiently understood. Second, limited attention has been given to the contextual conditions that may strengthen or weaken this relationship. This study constructs a balanced panel dataset covering 31 provincial-level regions in China from 2011 to 2024 to examine the relationship between digital economic transformation and green energy efficiency. Drawing on diffusion of innovations theory, the study examines technology diffusion as a potential transmission mechanism and investigates whether trade exposure to RCEP partner economies and environmental regulation condition this relationship. The analysis employs two-way fixed-effects models, mediation and moderation analyses and system generalised method of moments (GMM) estimation. Digital economic transformation is positively associated with green energy efficiency and its coefficient remains positive in the system GMM robustness model. The estimated indirect effect through technology diffusion is 0.028; the Sobel test yields z = 1.68 (p = .094). Thus, *H2* is not supported at the conventional 5% level, although the estimate provides marginal evidence at the 10% level. Stronger environmental regulation and greater trade exposure to RCEP partner economies are associated

with a stronger positive relationship between digital economic transformation and green energy efficiency. These findings suggest that the environmental benefits of digital development do not arise automatically. Policy should therefore integrate digital investment with technology diffusion, effective environmental governance and deeper regional low-carbon cooperation.

1. Introduction

China's shift towards greener and lower-carbon growth is taking place alongside tighter global climate governance and continuing changes in regional economic relations. Green energy efficiency reflects not only the use of energy inputs, but also the balance between economic output and environmental pressure. It is therefore closely related to energy-structure adjustment and emission-reduction targets (Zakari et al., 2022). In recent years, digital infrastructure, industrial digitalisation, industrial Internet applications and digital energy-management systems have been increasingly used in energy production, allocation and consumption. These changes provide new technical support for improving energy use, reducing resource misallocation and promoting greener forms of development (Hu et al., 2024; Si et al., 2024; Yu & Hu, 2024). A key question, therefore, is whether digital economic transformation can raise green energy efficiency and how such an effect is generated.

Existing research has widely discussed the links between digitalization, green development, energy performance and low-carbon transition. However, two issues remain insufficiently addressed. First, the pathway from digital economic transformation to green energy efficiency has not been fully explained. Technology diffusion may be an important route through which the productivity and environmental benefits of digital transformation are transferred to the energy sector, yet this channel has received relatively limited attention (Wang & Xu, 2023; Yuan & Zhang, 2020; Zanello et al., 2016). Second, the role of contextual conditions is yet to be clarified. Notably, few studies jointly examine trade exposure to RCEP partner economies and domestic environmental regulation as conditions shaping this association. Thus, while the current body of research provides some insight, it has not completely explained why and how the association between digitalisation and green energy efficiency differs across regions or contexts (Sheng et al., 2026; Wang & Xu, 2023; Yuan & Zhang, 2020). Using balanced panel data for 31 provincial-level regions in China from 2011 to 2024, this paper investigates the relationship between digital economic transformation and green energy efficiency. It then examines whether technology diffusion may serve as an indirect pathway and whether environmental regulation and trade exposure to RCEP partner economies moderate this association.

This paper contributes to the literature in three aspects. Firstly, it puts digital upgrading, technology diffusion, environmental stringency and regional openness into one integrated empirical setting to account for differences in green energy outcomes across provinces. Secondly, instead of directly associating digitalisation with efficiency, we consider technology diffusion as one potential way through which digital capabilities translate to energy-efficiency improvement. Thirdly, by taking into account external exposure in regional trade and domestic environmental regulation at the same time, we provide a better understanding of the institutional environment where digital transformation would give rise to more pronounced green energy benefits.

2. Literature review

2.1 Digital economic transformation and green energy efficiency

A substantial body of earlier literature recognises that the expansion of the digital economy contributes to improvements in overall environmental quality and energy-system performance, through more efficient

resource allocation and energy utilisation alongside green technological innovation (Gao et al., 2022; Wu, J. et al., 2023). These benefits typically arise through three overlapping, mutually reinforcing pathways: efficient resource allocation, precise energy management and stronger innovative capacity. Recent JIBE research also links digital-economy adoption and green innovation with competitiveness and low-carbon outcomes in emerging-economy settings (Halim et al., 2026; Qiu et al., 2025).

Digital infrastructure increases the velocity of information flow, improves data accuracy and tightens connections across the whole energy system. Automated data collection, real-time performance monitoring and integrated control systems enable energy suppliers and users to identify trouble spots faster, balance supply and demand more accurately and cut down on information asymmetry, allocation mismatches and waste.

More specifically for the manufacturing sector, industrial digitalisation is transforming traditional production processes by deploying intelligent machinery, interconnected platforms and data-driven management practices. The implementation of Industrial Internet of Things (IIoT) networks and digital energy platforms improves monitoring accuracy, strengthens links across production chains and supports real-time management responses (Hu et al., 2024), enabling firms to manage production more efficiently, reduce unnecessary energy use and adopt cleaner production practices.

Third, digital innovation enables the integration of digital technologies with green technologies, energy technologies and management systems so as to shorten the green technology development cycle and the diffusion process of green technologies in enterprises and regions and promote their application. In this way, digital economic transformation offers technical support for continuously improving green energy efficiency (Huang & Lin, 2024; Li et al., 2022; Lyu et al., 2025).

Nevertheless, much empirical research on the environmental consequences of digitalisation has focused on green total factor productivity, carbon performance or broad green-development indicators. By contrast, green energy efficiency has been examined less frequently, although it jointly reflects energy use, economic output and environmental costs. This limitation makes it difficult to determine whether digital economic transformation directly improves energy-use efficiency when environmental constraints are considered (Gao et al., 2022; Li et al., 2023; Wu, M., 2023). Accordingly, the first hypothesis is formulated as follows:

H1: Digital economic transformation is positively associated with green energy efficiency.

2.2 Mediating role of technology diffusion

Drawing on diffusion of innovations theory, technology diffusion is understood as the process through which technological achievements generate productivity and environmental benefits after they are transferred, adopted and adapted through learning, imitation, market exchange and collaboration (Rogers, 2003; Zanello et al., 2016). In green energy transition, diffusion can speed up the application of energy-saving equipment, clean-production technologies and renewable-energy solutions. It can also reduce the cost of adopting green technologies, improve energy-system operation and support the movement of energy-intensive sectors towards lower-carbon production (Xu et al., 2024).

Digital economic transformation may strengthen the conditions for such diffusion. Digital infrastructure and data platforms reduce the costs of searching for, identifying and matching technological information, allowing technology suppliers and users to connect more efficiently. Digital networks and online platforms also expand the channels through which green technologies move across regions and become commercial applications. Moreover, digitalisation may strengthen the absorptive capacity within firms and regions, making external technologies easier to recognise, assimilate and reuse. This argument is consistent with evidence that digital capability promotes innovation performance through stronger knowledge-absorption capabilities, which allow organisations to acquire, assimilate and apply knowledge from outside sources

more effectively (Kastelli et al., 2024; Wang et al., 2022; Yin et al., 2022). Digitalisation of the economic system may therefore improve green energy efficiency by facilitating technology diffusion. Accordingly, the second hypothesis is stated as follows:

H2: Technology diffusion mediates the relationship between digital economic transformation and green energy efficiency.

2.3 Moderating role of the institutional environment

Trade exposure to RCEP partner economies captures how closely a province is connected through trade to the 14 RCEP economies other than China. Because this trade relationships existed before the Agreement entered into force, the construct reflects an external trade-exposure condition rather than RCEP policy implementation. Greater trade exposure may facilitate cross-border flows of digital technologies, energy-saving equipment, green production practices and managerial knowledge. Research on renewable-energy trade networks in the RCEP region indicates that regional trade ties can support the circulation of energy-related resources and knowledge among participating economies (Tian et al., 2024). Such flows may strengthen the capacity of firms and local governments to use digital tools in energy monitoring, production optimisation and resource allocation, thereby increasing the green-energy gains associated with digital economic transformation (Wang & Xu, 2023; Zreik, 2024).

Accordingly, the positive association between digital economic transformation and green energy efficiency is expected to be stronger where trade exposure to RCEP partner economies is higher.

*H3*a: The positive association between digital economic transformation and green energy efficiency is stronger at higher levels of trade exposure to RCEP partner economies.

Environmental regulation is an important component of domestic institutional governance and may influence how far digital economic transformation improves green energy efficiency. Stricter regulation increases the compliance costs of energy-intensive and pollution-intensive activities, which can encourage cleaner production, energy conservation and environmentally oriented innovation. Previous studies have also related green technological innovation and environmental regulation to better energy-environmental efficiency (Hao et al., 2022; Li et al., 2023). When regulatory pressure is stronger, digital technologies are more likely to be used for process optimisation, real-time energy management, emissions monitoring and pollution reduction. These applications can improve the precision of environmental governance and reinforce the efficiency gains associated with digital transformation (Li et al., 2022; Wu, M., 2023). Recent evidence further indicates that institutional factors and environmental policy can strengthen sustainability initiatives (Musa et al., 2026).

Accordingly, environmental regulation may strengthen the association between digital economic transformation and green energy efficiency by increasing regulatory pressure and incentives for green production and digital environmental management.

*H3*b: Environmental regulation positively moderates the association linking digital economic transformation with green energy efficiency.

3. Methodology

3.1 Samples and data sources

This paper constructs a balanced provincial panel for the period 2011–2024 to examine how digital economic transformation relates to green energy efficiency in China. The analytical sample includes 31 mainland provincial administrative units. We exclude Hong Kong, Macao and Taiwan from this dataset because their statistical systems and data availability differ substantially from those of mainland provinces and are not directly comparable.

Our study employs a balanced panel that exploits cross-regional and temporal variations. This design enables us to account for long-standing, time-invariant disparities across regions in resource endowments, industrial foundations and institutional environments. This structure is appropriate for identifying the relationships among digital economic transformation, green energy efficiency, technology diffusion and the institutional environment (Hsiao, 2022).

The dataset is compiled from official and specialised materials drawn from statistics issued by the National Bureau of Statistics of China, CEADs carbon-emission data, administrative records from the Ministry of Industry and Information Technology and the China National Intellectual Property Administration, together with the China Technology Market Statistical Yearbook, the China Environmental Statistics Yearbook, customs information and statistical yearbooks released by individual provinces. Accordingly, the calculation of green energy efficiency uses indicators related to energy use and the capital stock, labour utilisation, regional economic output, together with carbon dioxide emissions. Provincial carbon-emission data are mainly benchmarked against CEADs where provincial observations are available; for more recent years, the observations are completed and checked against official energy statistics, provincial statistical materials and a consistent accounting procedure. Data on digital economic transformation, technology diffusion, trade exposure to RCEP partner economies, environmental regulation and the control variables are collected from official databases, statistical yearbooks and government bulletins. Before estimation, data from different sources are matched by province and year, while inconsistent definitions are reviewed and harmonised to improve comparability across regions and over time.

3.2 Definition of variables

The empirical framework includes variables for the direct, mediating and moderating relationships examined in this study. Green energy efficiency (GEE) is the dependent variable. It measures a province's ability to produce economic output while restraining energy consumption and environmental damage. The indicator is calculated using a super-efficiency slacks-based measure data envelopment analysis (SBM-DEA) specification. The SBM framework incorporates input as well as output slacks in efficiency assessment, while the super-efficiency extension enables efficient decision-making units to be ranked further (Tone, 2002). Energy consumption, capital stock and labour are used for the input vector; gross domestic product represents the desirable output, whereas carbon dioxide emissions are treated as an undesirable output. For regression comparability across provinces and years, the resulting scores are normalised to the 0–1 interval. This specification allows the indicator to reflect both productive performance and environmental cost (Wang et al., 2024).

Digital economic transformation is treated as the principal explanatory variable and is quantified by a multidimensional indicator covering information-technology infrastructure, industrial digitalisation and digital innovation. To maintain comparability over the full study period, the index uses indicators with continuous provincial coverage, including mobile communication infrastructure, Internet penetration, broadband access, industrial digitalisation, digital-service development, digital-related R&D, digital technology patents and digital standards. These indicators describe the digital foundation of each province, the use of digital technologies in industrial activities and the capacity for digital knowledge creation (Miao, 2021; Wang et al., 2021).

As the core mediating variable, technology diffusion is proxied by the average value of individual technology transactions. This indicator is calculated by dividing the total transaction value of regional technology markets by the number of technology contracts. It captures the extent to which technological achievements circulate through local technology markets and generate commercial value, although it cannot fully reflect informal or non-market channels of technology diffusion (National Bureau of Statistics of China & Ministry of Science and Technology of China, 2019).

We introduce two moderating variables to capture contextual conditions: trade exposure to RCEP partner economies and environmental regulation. Trade exposure to RCEP partner economies (RTE) is measured as the sum of province i's exports to and imports from the 14 RCEP partner economies other than China, divided by the province's total exports plus total imports in year t. A fixed partner set—the ten ASEAN member states, Japan, the Republic of Korea, Australia and New Zealand—is applied to every year from 2011 to 2024. RCEP entered into force for China on 1 January 2022 (Ministry of Commerce of the People's Republic of China, 2021). Accordingly, RTE values for 2011–2021 represent pre-existing trade exposure to economies that subsequently became RCEP parties, whereas values for 2022–2024 represent the same trade-share measure after the Agreement entered into force for China. The indicator includes no post-RCEP treatment dummy, tariff-concession measure or treated-control comparison. It therefore measures trade exposure rather than the causal policy effect of RCEP implementation. Provincial environmental regulatory intensity is proxied by investment in industrial pollution control per one thousand yuan of industrial value added. It reflects the resources that regions invest in pollution control and environmental protection.

To ensure the robustness of the core relationship, we include four control variables: the natural logarithm of per capita GDP, the natural logarithm of investment in the energy industry, trade openness and the natural logarithm of the urban population. These variables control for the differences between provinces in economic development, energy industry capital investment, trade openness and population distribution. Detailed variable definitions and measurement methods are presented in Table 1.

Table 1. Variable definitions and measurements

Variable type	Variable name	Symbol	Measurement	Data source
Dependent variable	Green energy efficiency	GEE	Calculated using the super-efficiency SBM-DEA model. Inputs include energy consumption, capital stock and labour. Desirable output is regional GDP and undesirable output is CO_2 emissions. The final scores are normalised to 0-1 for regression analysis.	National Bureau of Statistics; CEADs; provincial statistical yearbooks
Mediating variable	Technology diffusion	TD	Average transaction value in the technology market, calculated by dividing total technology-market transaction value by the number of technology contracts.	National Bureau of Statistics; China Technology Market Statistical Yearbook
Moderating variable	Trade exposure to RCEP partner economies	RTE	Share of a province's exports to and imports from the 14 RCEP partner economies other than China in its total exports plus imports; a fixed partner set is used for 2011–2024.	General Administration of Customs; provincial statistical yearbooks

Variable type	Variable name	Symbol	Measurement	Data source
Core explanatory variable	Digital economic transformation	DET	Composite index of digital economic development covering digital infrastructure, industrial digitalisation and digital innovation. Indicators include mobile communication infrastructure, Internet penetration, broadband access, industrial digitalisation, digital-service development, digital-related R&D, digital technology patents and digital standards.	MIIT; National Bureau of Statistics; CEIC; China National Intellectual Property Administration; Standardization Administration of China
Moderating variable	Environmental regulation	ERI	Industrial pollution-control investment divided by industrial value added, expressed per thousand yuan.	China Environmental Statistics Yearbook; provincial statistical yearbooks
Control variable	GDP per capita	PGDP	Natural logarithm of GDP per capita.	National Bureau of Statistics; provincial statistical yearbooks
Control variable	Energy-industry investment	EII	Natural logarithm of investment in the energy industry or comparable energy-sector investment indicator.	National Bureau of Statistics; provincial statistical yearbooks
Control variable	Trade openness	OPEN	Total imports and exports as a share of regional GDP, expressed in percentage terms.	National Bureau of Statistics; General Administration of Customs; provincial statistical yearbooks
Control variable	Urban population	UP	Natural logarithm of permanent urban population.	National Bureau of Statistics; provincial statistical yearbooks

3.3 Model setting

The empirical analysis first uses a two-way fixed-effects model to estimate the direct association between digital economic transformation and green energy efficiency. In line with panel-data estimation, the model controls for province-specific heterogeneity and year-specific shocks (Hsiao, 2022). The baseline specification is:

$$GEE_{it} = \alpha_0 + \alpha_1 DET_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

In Equation (1), GEE_it represents green energy efficiency for province i in year t, DET_it represents digital economic transformation and X_it denotes the control-variable vector comprising per capita GDP,

energy-industry investment, trade openness and urban population. The terms μ_i and λ_t denote province and year fixed effects, respectively and ε_it is the disturbance term. The coefficient α_1 is interpreted as the conditional association between digital economic transformation and green energy efficiency after accounting for time-invariant provincial characteristics and common annual shocks.

The mediation models examine whether technology diffusion serves as a pathway through which digital economic transformation is linked to green energy efficiency. The following specifications are estimated:

$$TD_{it} = \beta_0 + \beta_1 DET_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$
$$GEE_{it} = \delta_0 + \delta_1 DET_{it} + \delta_2 TD_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In Equations (2) and (3), TD_it represents technology diffusion. The indirect effect is defined as the product of path a—the coefficient linking digital economic transformation to technology diffusion—and path b—the coefficient linking technology diffusion to green energy efficiency conditional on digital economic transformation. To evaluate whether the indirect effect differs from zero, this study uses the Sobel (1982) test. The Sobel z-statistic is calculated by dividing the product ab by its delta-method standard error. The reduction in the coefficient of digital economic transformation after technology diffusion is included is reported descriptively and is not treated as sufficient evidence of mediation. Because the product of two coefficients may depart from normality, the Sobel result is interpreted as an asymptotic test (MacKinnon et al., 2002).

Two interaction models are then estimated to determine whether contextual conditions change the strength of the digitalisation-efficiency association. One model examines environmental regulation and the other examines trade exposure to RCEP partner economies:

$$GEE_{it} = \theta_0 + \theta_1 DET_{it} + \theta_2 ERI_{it} + \theta_3 (DET_{it} \times ERI_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$
$$GEE_{it} = \varphi_0 + \varphi_1 DET_{it} + \varphi_2 RTE_{it} + \varphi_3 (DET_{it} \times RTE_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

In Equations (4) and (5), ERI_it denotes environmental regulation and RTE_it denotes trade exposure to RCEP partner economies. A positive and statistically significant interaction term indicates that the association between digital economic transformation and green energy efficiency is stronger at higher levels of the relevant moderator. RTE_it retains the same trade-share construction throughout 2011–2024: values for 2011–2021 capture pre-existing exposure to the fixed set of partner economies and values for 2022–2024 capture the same exposure measure after RCEP entered into force for China. Consequently, the coefficient on DET_it × RTE_it estimates exposure-based moderation; it does not estimate the direct policy effect of RCEP implementation.

As a robustness check, an additional system GMM model is estimated to examine whether the baseline association remains positive in a dynamic specification that includes lagged green energy efficiency. The estimator follows the dynamic-panel GMM literature and uses lagged values as internal instruments (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). The model is specified as follows:

$$GEE_{it} = \rho GEE_{i,t-1} + \eta DET_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

The dynamic specification in Equation (6) adds the first lag of green energy efficiency to capture persistence in the dependent variable. The AR(1), AR(2) and Hansen statistics are reported as model diagnostics. The empirical analysis proceeds from descriptive statistics to the baseline fixed-effects model, the mediation and moderation tests and, finally, the dynamic-panel robustness model. This sequence evaluates the national-average association, the proposed indirect pathway, the two moderating relationships and the stability of the digital economic transformation coefficient across model specifications.

4. Findings and Discussion

Table 2 summarises the distribution of the study variables. Green energy efficiency and digital economic transformation vary substantially across provincial observations, indicating meaningful regional heterogeneity. Technology diffusion, trade exposure to RCEP partner economies and environmental regulation also display considerable dispersion. The control variables likewise vary across provinces in economic development, energy-sector investment, trade openness and population scale. This cross-sectional and temporal variation supports the use of panel models that account for persistent provincial characteristics and common year-specific shocks.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Green energy efficiency	434	0.550	0.166	0.213	1.000
Digital economic transformation	434	0.573	0.323	0.001	1.000
Technology diffusion	434	0.173	0.135	0.100	1.000
Trade exposure to RCEP partner economies	434	0.218	0.181	0.100	0.984
Environmental regulation	434	0.218	0.124	0.100	1.000
GDP per capita	434	10.927	0.482	9.682	12.338
Energy-industry investment	434	6.608	0.863	4.094	8.567
Trade openness	434	17.684	1.723	12.646	20.971
Urban population	434	7.602	0.906	4.248	9.179

4.1 Benchmark regression results

Table 3 presents the outcomes of benchmark regression estimations. Model 1 only incorporates year fixed effects; the estimated coefficient for digital economic transformation shows a negative value without statistical significance. For Model 2, which solely controls provincial fixed effects, the sign of this coefficient turns positive while remaining insignificant statistically. When both province and year fixed effects are included in Model 3, the coefficient is 0.214 and statistically significant. These results indicate a positive association between digital economic transformation and green energy efficiency after controlling for time-invariant provincial characteristics and common year shocks.

Turning to the control variables, per capita GDP and trade openness both have positive and statistically significant coefficients in Model 3. The signs and significance of energy-industry investment and urban population vary across specifications. After province and year fixed effects are included, the coefficient of digital economic transformation is positive and statistically significant, which is consistent with *H1*.

Table 3. Benchmark regression

Variables	Model 1	Model 2	Model 3
Digital economic transformation	-0.151(-1.94)	0.034(0.37)	0.214**(3.19)
GDP per capita	0.185***(6.43)	0.285*(2.22)	0.405***(5.07)

Variables	Model 1	Model 2	Model 3
Energy-industry investment	0.033***(3.73)	-0.009(-0.41)	-0.006(-0.66)
Trade openness	-0.009(-0.86)	0.063*(2.24)	0.064***(4.68)
Urban population	0.045**(2.71)	-0.399*(-2.38)	-0.405***(-5.19)
Constant	-1.790***(-7.27)	-0.614(-0.55)	-1.825**(-2.62)
R^2	0.4559	0.5103	0.5455
F	47.82***	13.12***	25.67***
Year fixed effects	Yes	No	Yes
Province fixed effects	No	Yes	Yes

Note: *** p < .001, ** p < .01, * p < .05. t-statistics are reported in parentheses.

4.2 Mediation analysis of technology diffusion

Table 4 reports the mediation regressions. In the baseline green energy efficiency model, the coefficient of digital economic transformation is 0.214 and statistically significant. When technology diffusion is the dependent variable, the coefficient of digital economic transformation is 0.111 and is significant only at the 10% level. The first-stage association is therefore weak and should be interpreted cautiously.

When digital economic transformation and technology diffusion are included simultaneously in the green energy efficiency model, the coefficient of technology diffusion is 0.255 and statistically significant at the 1% level. The coefficient of digital economic transformation declines from 0.214 to 0.186 and remains statistically significant. This coefficient reduction is descriptive and does not by itself establish mediation. The estimated indirect effect is 0.028 (0.111 × 0.255). The Sobel test yields z = 1.68 (p = .094), indicating that the indirect effect does not reach the conventional 5% significance threshold. *H2* is therefore not supported at the 5% level, although the estimate provides marginal evidence at the 10% level.

Table 4. Mediation regression results for technology diffusion

Variables	GEE	TD	GEE
Digital economic transformation	0.214**(3.19)	0.111+ (1.79)	0.186**(2.83)
Technology diffusion			0.255***(4.71)
GDP per capita	0.405***(5.07)	0.015(0.20)	0.401***(5.16)
Energy-industry investment	-0.006(-0.66)	0.054***(6.57)	-0.020*(-2.14)
Trade openness	0.064***(4.68)	0.028*(2.22)	0.057***(4.24)
Urban population	-0.405***(-5.19)	-0.277***(-3.88)	-0.334***(-4.31)
Constant	-1.825**(-2.62)	1.195(1.88)	-2.130**(-3.13)
R^2	0.5455	0.5418	0.5703
F	25.67***	25.29***	26.83***
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes

Note: *** p < .001, ** p < .01, * p < .05, + p < .10. t-statistics are reported in parentheses

Table 5. Sobel test of the indirect effect through technology diffusion

Variables	Indirect effect	z-statistic	p-value
Sobel test	0.028	1.68	0.094

Note: The indirect effect is the product of path coefficients a and b, where a links digital economic transformation to technology diffusion and b links technology diffusion to green energy efficiency conditional on digital economic transformation. The Sobel z-statistic is the ratio of the indirect effect to its delta-method standard error.

4.3 Moderating effect of the institutional environment

Table 6 reports the moderation estimates. In the environmental regulation model, the interaction between digital economic transformation and environmental regulation is positive and statistically significant (coefficient = 0.539). The estimated association between digital economic transformation and green energy efficiency is therefore stronger at higher levels of environmental regulation, which is consistent with *H3*b.

In the RCEP-related trade-exposure model, the interaction between digital economic transformation and trade exposure to RCEP partner economies is positive and statistically significant (coefficient = 0.538). The estimated association between digital economic transformation and green energy efficiency is therefore stronger in province-year observations with greater trade exposure to RCEP partner economies. Because RTE is a continuous trade-share measure with the same construction throughout 2011–2024, the coefficient represents exposure-based moderation rather than the direct policy effect of RCEP implementation. The result is consistent with *H3*a.

Table 6. Moderating effect

Variables	Model 1 (ERI)	Model 2 (RTE)
Digital economic transformation	0.213(1.37)	0.211(1.46)
Environmental regulation	-0.049(-0.91)	
Digital economic transformation × Environmental regulation	0.539*(2.56)	
Trade exposure to RCEP partner economies		0.221**(2.88)
Digital economic transformation × trade exposure to RCEP partner economies		0.538**(2.61)
GDP per capita	0.478**(3.01)	0.495**(3.13)
Energy-industry investment	-0.009(-0.42)	-0.011(-0.54)
Trade openness	0.048(1.69)	0.046(1.74)
Urban population	-0.436*(-2.52)	-0.444**(-2.74)
Constant	-1.961(-1.52)	-2.017(-1.65)
R^2	0.5689	0.5905
F	16.05***	31.18***

Variables	Model 1 (ERI)	Model 2 (RTE)
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes

Note: *** p < .001, ** p < .01, * p < .05. t-statistics are reported in parentheses.

4.4 Robustness test

The robustness analysis examines whether the baseline association remains positive in a dynamic panel specification that includes lagged green energy efficiency. A system GMM model is estimated using lagged values as internal instruments. Given the relatively small provincial cross-section, the estimates are interpreted as a robustness check rather than as definitive causal identification.

The system GMM model contains 403 observations because the dynamic specification includes a one-period lag of the dependent variable. Table 7 shows that the coefficient of lagged green energy efficiency is 0.964 and statistically significant, indicating strong temporal persistence. The coefficient of digital economic transformation remains positive and statistically significant at the 5% level (coefficient = 0.041). This result is consistent with the positive association in the baseline model under the reported dynamic specification.

The AR(1) test is statistically significant (p = .020), while the AR(2) test is not (p = .184). The Hansen test is also not statistically significant (p = .548). These diagnostics do not reject the reported specification at conventional levels, but they do not by themselves establish instrument validity or causal identification. Overall, the system GMM estimate is directionally consistent with the benchmark fixed-effects result.

Table 7. System GMM robustness results

Variables	System GMM model
L. Green energy efficiency	0.964***(17.31)
Digital economic transformation	0.041*(2.29)
GDP per capita	-0.010(-0.48)
Energy-industry investment	-0.002(-0.31)
Trade openness	0.007(0.95)
Urban population	0.008(0.69)
Constant	-0.044(-0.25)
Year fixed effects	Yes
Province-specific effects handled	Yes
AR(1)	0.020
AR(2)	0.184
Hansen	0.548
Observations	403
Groups	31

Note: *** p < .001, ** p < .01, * p < .05. Test statistics are reported in parentheses. Year dummy variables are included to control for common time shocks and province-specific effects are handled

through the dynamic panel transformation. AR(1), AR(2) and Hansen entries are p-values used to assess serial correlation and instrument validity.

4.5 Discussion

The estimates indicate a positive association between digital economic transformation at the provincial level and green energy efficiency across the sample. This finding is consistent with observed practices in which digital infrastructure and industrial digital applications are widely used for energy monitoring, production scheduling and environmental management. It also echoes findings from previous studies on digitalisation, low-carbon development and energy-use efficiency (Li et al., 2022; Wang et al., 2022; Huang & Lin, 2024). A key strength of the analysis is its use of green energy efficiency as the dependent variable, which jointly captures energy use, economic output and environmental losses.

Three interrelated mechanisms may help explain this empirical relationship. Digital infrastructure deployment, industrial digital upgrading and digital innovation can collectively improve the efficiency of energy utilisation, streamline internal production processes and accelerate the adoption and application of green technologies (Li et al., 2022; Wang et al., 2022; Huang & Lin, 2024). This pattern may arise because digitalisation is changing how businesses collect, process and use energy-related information. Faster information transmission and real-time monitoring can facilitate the early detection of inefficient energy use in businesses. Industrial digitalisation can improve the accuracy of production planning and process control, thereby reducing avoidable energy consumption.

Digital innovation may reduce barriers to the development, matching and deployment of green technologies and intelligent energy-management tools. However, the mediation analysis does not establish an indirect effect at the conventional 5% level. The Sobel result provides only marginal evidence at the 10% level that technology diffusion may be involved in the association between digital economic transformation and green energy efficiency. Digital platforms and data networks can reduce search and matching costs and facilitate the transfer of technological knowledge, thereby supporting the adoption and diffusion of environmentally friendly technologies, energy-saving equipment and managerial practices (Rogers, 2003; Xu et al., 2024; Zanello et al., 2016).

Digitalisation therefore does not operate in isolation; its environmental benefits may depend partly on whether local institutions encourage firms and governments to use digital tools for energy management and pollution control. This interpretation is consistent with evidence that regional economic linkages can facilitate green technology and knowledge flows, while environmental regulation can strengthen the environmental benefits associated with digital development (Tian et al., 2024; Wang & Xu, 2023; Wu, 2023; Zreik, 2024).

Overall, digital economic transformation is positively associated with green energy efficiency. The Sobel test provides only marginal evidence at the 10% level for an indirect pathway through technology diffusion, while greater trade exposure to RCEP partner economies and stricter environmental regulation are associated with a stronger digitalisation-efficiency relationship. This study extends previous research on green total factor productivity, carbon performance and broader green-development indicators by focusing specifically on green energy efficiency, which jointly reflects energy use, economic output and environmental costs.

5. Conclusion

This paper examines the association between digital economic transformation and green energy efficiency, focusing on the possible indirect role of technology diffusion and the conditioning roles of trade exposure to RCEP partner economies and environmental regulation, using provincial panel data for China

from 2011 to 2024. Across province- and year-fixed-effects estimates, mediation and moderation tests and system GMM estimation, the study provides broadly consistent evidence of a positive association between digital economic transformation and green energy efficiency. The positive coefficient is also retained in the system GMM robustness model.

The estimated indirect effect through technology diffusion is 0.028 and the Sobel test yields $z = 1.68$ ($p = .094$). The indirect effect therefore does not reach the conventional 5% significance threshold. *H2* is not supported at the 5% level, although the estimate provides marginal evidence at the 10% level. The moderation results indicate that the positive association between digital economic transformation and green energy efficiency is stronger in province-year observations with greater trade exposure to RCEP partner economies and stricter environmental regulation. The RTE interaction is interpreted as exposure-based moderation rather than as the direct policy effect of RCEP implementation.

These findings indicate that digital investment alone does not guarantee higher green energy efficiency. Digital capacities need to be supported by active technology markets, effective environmental governance and deeper regional low-carbon cooperation. Accordingly, policy should emphasise the development of stronger technology trading platforms, improved matching between green technology supply and demand, expanded digital environmental monitoring and greater cooperation in green equipment, technical standards and low-carbon industrial-chain development.

This study has several limitations. Provincial-level data may not fully capture differences in enterprise-level digital adoption, green investment or absorptive capacity. Future research could therefore employ enterprise- or industrial-park-level data, conduct cross-country comparisons among RCEP members and use policy shocks, external instrumental variables or quasi-natural experimental designs to strengthen causal identification.

Data Availability

The data supporting the findings of this study were compiled from publicly available official sources, including the National Bureau of Statistics of China, CEADs, the Ministry of Industry and Information Technology, the China National Intellectual Property Administration, relevant statistical yearbooks, the General Administration of Customs and provincial statistical yearbooks and bulletins. The processed panel dataset is available from the corresponding author upon reasonable request.

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Ethics Approval

Not applicable. This study uses publicly available secondary provincial-level statistical data and does not involve human participants or animals.

Conflict of Interest

The authors declare that they have no commercial, financial, personal or other conflicts of interest that could have influenced the design, conduct or reporting of this research.

Author Contributions

Shuangyan Zhou: Conceptualization, methodology, data collection, formal analysis, investigation, visualization and writing – original draft.

Au Yong Hui Nee: Supervision, conceptualization, validation and writing – review & editing.

Abdelhak Senadjki: Supervision, methodology, validation and writing – review & editing.

All authors reviewed and approved the final manuscript.

Disclosure of AI Use

Generative AI tools were used only for language editing, grammatical correction, readability improvement and manuscript formatting. All outputs were reviewed and verified by the authors, who remain fully responsible for the accuracy originality and integrity of the manuscript.

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