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Digitalisation and the Renewable-Energy Share: Evidence From 156 Countries, 2010–2022

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ABSTRACT

Digitalisation has become an important component of the energy transition by improving information exchange, system coordination, and technological innovation. However, its relationship with renewable-energy deployment remains complex because digital technologies can generate both enabling effects and additional energy demand. This study investigates the association between national digital-system capacity and renewable-energy transition using an unbalanced panel of 156 countries from 2010 to 2022. A multidimensional digitalisation index is constructed using entropy-weighted TOPSIS based on six indicators covering digital connectivity, infrastructure, and technology-related productive capacity. Renewable-energy transition is measured by the renewable-energy share in total final energy consumption, corresponding to Sustainable Development Goal (SDG). The empirical analysis combines fixed-effects models, common-correlated-effects estimation, dynamic-panel specifications, alternative index constructions, and spatial models to examine the robustness and contextual dependence of the relationship. The results show that higher digital-system capacity is positively associated with renewable-energy share in country fixed-effects models. A 0.1-point increase in the digitalisation index corresponds to approximately 3.9% higher renewable-energy share. The estimated association becomes smaller after accounting for common time variation and unobserved common factors, highlighting the importance of distinguishing national digital development from broader international trends. Formal interaction tests further reveal stronger associations in high-emissions contexts and significant differences across income groups. A CO_2-related pathway decomposition identifies a significant emissions-related component, while the result is interpreted as a contemporaneous relationship rather than causal mediation. Overall, the findings indicate that digitalisation can contribute to renewable-energy transition, but its effectiveness depends on technological diffusion, structural conditions, and the characteristics of national energy systems.

1 | Introduction

Expanding renewable energy is central to climate mitigation and energy security, but the transition involves more than adding renewable generating capacity (Cong et al. 2026). A higher renewable share in final energy consumption requires generation, grids, storage, market institutions, and end-use sectors to adjust together. This coordination problem becomes more demanding as variable wind and solar power enter electricity systems and as renewable energy must also replace fossil fuels in heating and transport (IEA 2024; IPCC 2018). The renewable-energy share in total final energy consumption, formalised as Sustainable Development Goal indicator, captures this economy-wide consumption outcome and permits comparison across countries (IEA et al. 2024).

Digitalisation may alter this transition through several, potentially opposing, channels. Digital communication, sensing, data processing, and automated control can improve load forecasting, grid monitoring, demand response, distributed-resource coordination, and energy transactions (Ahmad et al. 2021; IEA 2017). These functions may help energy systems accommodate a larger renewable contribution. Digital infrastructure, however, also consumes electricity and materials, while efficiency improvements can induce additional demand (Che et al. 2024; Hojnik et al. 2025). The growing energy footprint of data centres and computing therefore means that digital expansion is not inherently low-carbon (Briglauer et al. 2023; de Vries 2023). Whether broader national digital capacity is associated with renewable substitution is consequently an empirical question rather than a technological presumption.

A growing cross-country literature reports positive associations between information and communication technology (Fambeu and Yomi 2024; Lee et al. 2023), digital-economy development (Liu et al. 2025; Shahbaz et al. 2022), and renewable-energy outcomes (Zheng and Zhang 2025). Two issues nevertheless complicate comparison across studies. First, measures ranging from individual information and communication technology (ICT) access indicators to composite digital-economy indices capture different parts of digital capacity (Balsalobre-Lorente et al. 2025). Second, digitalisation and renewable-energy use both display strong international trends. Country fixed-effects models control for time-invariant national characteristics but do not fully capture shared temporal changes across countries. Incorporating common time effects and common-factor approaches can therefore provide additional insights into whether the observed relationship mainly reflects domestic changes or wider international trends. In addition, differences across national contexts should be examined using formal interaction tests, since separate subgroup estimates cannot directly establish heterogeneous relationships.

This study examines an unbalanced panel of 156 countries from 2010 to 2022. National digital-system capacity is measured using an entropy-weighted TOPSIS index that integrates indicators of connectivity, digital infrastructure, and technology-related productive capability. The renewable-energy transition outcome is measured as the logarithm of renewable energy consumption as a share of total final energy consumption. The empirical framework evaluates the digitalisation–renewable-energy relationship from multiple perspectives. Baseline fixed-effects models are complemented by specifications accounting for common factors, dynamic adjustment, alternative digitalisation measures, and spatial dependence. Heterogeneity across emissions and income contexts is assessed through formal interaction models estimated using the full sample.

2 | Literature Review

2.1 | Measuring National Digital-System Capacity

Digitalisation is a multidimensional national capability rather than a single technology. Early empirical studies often relied on individual information and communication technology (ICT) indicators such as Internet access, broadband penetration, and mobile subscriptions, whereas more recent work increasingly adopts broader measures covering connectivity, digital infrastructure, services, and productive capability (Chen et al. 2023; Wang and Wang 2025). This distinction matters because single indicators capture specific aspects of digital development, while composite indices provide a broader representation of national digital capacity (Lee et al. 2023; Liu et al. 2025; Zheng and Zhang 2025).

The index used in this study combines six indicators with broad country-year coverage. Internet use, fixed-broadband subscriptions, and mobile-cellular subscriptions represent access and connectivity; secure Internet servers capture digital infrastructure; and ICT-service exports and high-technology exports reflect digital services and technology-related productive capability. Together, these indicators approximate three dimensions of national digital-system capacity: connectivity, secure service infrastructure, and ICT-related production (Wang and Wang 2025; Zheng and Zhang 2025).

The indicators are aggregated using entropy-weighted TOPSIS, which assigns greater weights to indicators with more variation across observations and evaluates each country-year relative to positive and negative ideal solutions. This approach has been applied to heterogeneous indicators in digitalisation and energy-related research (Al-Abadi et al. 2025; Zheng and Zhang 2025). Equal-weight and principal-component alternatives are also considered to assess sensitivity to index construction. The resulting index captures broad national digital-system capacity rather than the adoption of specific energy-sector technologies such as smart grids, digital metering, or utility automation.

2.2 | Enabling and Adverse Pathways

General-purpose-technology theory characterises digital technologies as pervasive inputs whose returns depend on complementary innovation by users (Bresnahan and Trajtenberg 1995). Applied to energy systems, connectivity has limited value without flexible networks, compatible equipment, organisational capability, and market rules (Lund et al. 2017). Ecological modernisation theory adds that technological change improves environmental performance through institutional reform and reorganisation rather than through technology alone (Mol and Spaargaren 2000). Relevant pathways include improved generation and load forecasting, demand response, distributed-resource coordination, predictive maintenance, lower transaction costs, and more timely monitoring (Ahmad et al. 2021; IEA 2017). Supply-chain digitalisation may also improve maintenance and coordination, although technology-ranking studies do not identify the same macro-panel relationship (Alyamani et al. 2026).

These mechanisms require complementary assets. Connectivity alone does not create flexible grids, interoperable markets, skilled operators, credible renewable-energy policy, access to finance, or enforceable data standards (Huang et al. 2025). Institutional quality and financial development can condition whether information becomes investment and operational change (Hwang and Venter 2025; Shahbaz et al. 2022). Research on financial development and natural-resource thresholds further shows that transition relationships can depend on structural conditions rather than a single technology variable (Hadj et al. 2025; Sahoo et al. 2024).

Digitalisation can also impede decarbonisation. Data centres, network equipment, and devices consume electricity and materials; efficiency gains may induce rebound effects; unequal access can concentrate benefits; and cybersecurity failures can reduce system reliability (de Vries 2023; Kim et al. 2026). The expected net association is therefore conditional and may be nonlinear. At low levels, connectivity and monitoring may relax binding constraints. At high levels, marginal benefits may diminish while digital demand continues to rise (Lange et al. 2020).

2.3 | Cross-Country Evidence and Unresolved Empirical Issues

Cross-country evidence generally links digital development to renewable-energy outcomes, but the estimated relationship varies with the empirical setting. Shahbaz et al. (2022) report that governance mediates the relationship between the digital economy and energy transition in a global sample. Lee et al. (2023) show that the association between ICT and renewable energy varies across the renewable-energy distribution and with country risk. Fambeu and Yomi (2024) identify economic growth and structural transformation as conditioning factors in Africa. Huang et al. (2025) further show that the contribution of digitalisation to sustainable development varies with financial development, energy transition and structural conditions across African economies. More recent global studies use broader digital-economy measures and examine renewable-energy development across large country samples (Liu et al. 2025; Zheng and Zhang 2025). Taken together, this literature supports neither a single digitalisation measure nor an invariant cross-country coefficient.

Part of the variation across findings reflects differences in the estimand. Renewable electricity generation, installed capacity, renewable-energy consumption, energy-transition indices, and the renewable share of final consumption describe related but non-equivalent outcomes (Gielen et al. 2019; IEA et al. 2024). Likewise, Internet penetration, ICT use, digital-economy indices, and energy-sector digitalisation capture different dimensions of digital development. These differences in measurement can lead studies to identify distinct aspects of the digitalisation–energy transition relationship. The present study therefore focuses specifically on the association between multidimensional national digital-system capacity and the renewable share of total final energy consumption.

A second source of variation is the treatment of common factors and country heterogeneity. Global technology costs, international standards, commodity prices, climate-policy diffusion, and macroeconomic shocks can move digitalisation and renewable-energy use in many countries at the same time (Baldwin et al. 2019; IRENA 2023). Country fixed effects do not absorb this shared time variation. Year fixed effects and common-correlated-effects specifications address it differently, and comparing them reveals how much of the estimated association depends on common movement (Pesaran 2006). Heterogeneity claims pose a related problem: separate significance levels across income or emissions groups do not establish that their coefficients differ. A unified interaction model is needed to test the cross-group contrast directly.

These issues define the remaining empirical task. Existing studies provide substantial evidence that digital variables and renewable-energy outcomes co-vary, but they leave uncertainty about whether the relationship survives alternative controls for common international variation, alternative constructions of a multidimensional digital index, and formal tests of contextual differences. The analysis below addresses those questions in one 156-country framework.

2.4 | Hypotheses

H1. *Higher national digital-system capacity is associated with a higher renewable-energy share, conditional on observed controls and country effects.*

This expectation follows from reduced information and coordination costs, but it is conditional on complementary energy infrastructure and policy (Lund et al. 2017). The competing prediction is weak or negative where digital electricity demand, rebound effects, or institutional constraints dominate (Lange et al. 2020).

H2. *Higher national digital-system capacity is associated with lower per-capita CO_2 emissions, which form a positive pathway to a higher renewable-energy share.*

The hypothesis is tested by decomposing the total digitalisation coefficient into a direct component and a CO_2-related coefficient product, with significance evaluated by country-block bootstrap.

H3. *The digitalisation association varies across development and emissions contexts.*

H3 is evaluated with formal interaction models that compare emissions and income contexts within the full sample. These two dimensions capture differences in transition pressure, infrastructure, institutional capacity, and fossil-fuel dependence (Baldwin et al. 2019; Lund et al. 2017). Figure 1 summarises the conceptual and empirical framework.

3 | Data and Methods

3.1 | Data, Sample, and Preprocessing

The data are drawn principally from the World Development Indicators, with the original telecommunications series supplied by the International Telecommunication Union. The initial panel contains 1927 observations for 160 codes over 2010–2022. AFE (Africa Eastern and Southern) and SST (Small States) are World Bank aggregates and are removed. Complete-case selection for the dependent variable, digitalisation index, controls, and per-capita CO_2 emissions yields 1875 observations for 156 countries. Montenegro and Palestine are excluded because their CO_2 series are entirely missing. The resulting panel is unbalanced, with country histories ranging from 4 to 13 years.

The preprocessing procedure follows three principles: retaining zero-valued observations where the logarithm is otherwise undefined, preserving each country's time ordering when filling internal gaps, and limiting the influence of extreme digital indicators.

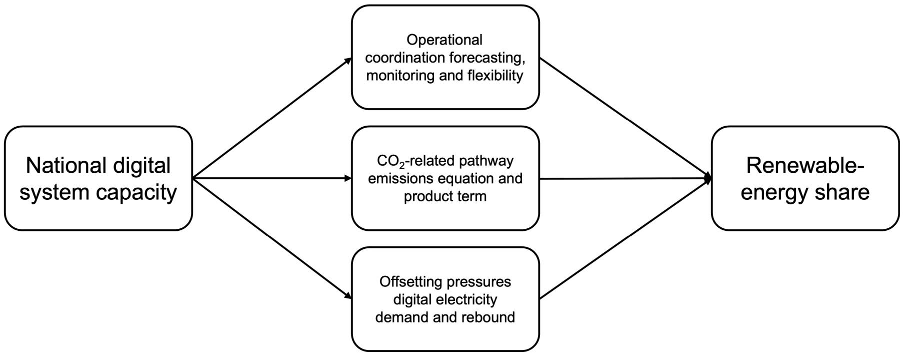

FIGURE 1 | Conceptual framework. The empirical models relate the national digitalisation index to the renewable-energy share and explore per-capita CO_2 emissions as an intermediate variable. Energy-system coordination, finance, institutions, digital demand, and rebound effects are interpretations or boundary conditions, not directly measured mechanisms.

Variables that can equal zero, including the renewable-energy share, natural-resource rents, and per-capita CO_2 emissions, are transformed as shown in Equation (1):

$$s_{it}^{\log} = \ln\left(s_{it} + 0.01\right) \tag{1}$$

Strictly positive controls are transformed as $s_{it}^{\log} = \ln\left(s_{it}\right)$. The constant 0.01 keeps zero observations in the sample and is small relative to the reported measurement units.

Missing observations inside a country's observed series are linearly interpolated. If s_{i,t_0} and s_{i,t_1} are the nearest observed values surrounding year t, the interpolated value is given by Equation (2):

$$\tilde{s}_{it} = s_{i,t_0} + \frac{t - t_0}{t_1 - t_0}\left(s_{i,t_1} - s_{i,t_0}\right), t_0 < t < t_1 \tag{2}$$

At the two series boundaries, the nearest observed country value is carried to the unobserved boundary year. This procedure uses only information from the same country and avoids replacing national trajectories with cross-country averages.

Before index construction, each digital subindicator is winsorised at the pooled 5th and 95th percentiles. For subindicator j, the adjusted value is given by Equation (3):

$$q_{ijt}^{W} = \min\left\{Q_{j,0.95}, \max\left(Q_{j,0.05}, q_{ijt}\right)\right\}. \tag{3}$$

Pooled cut-offs apply a common benchmark to all country-years and reduce the leverage of extreme observations without deleting countries from the panel.

Additional details on sample construction, variable transformations, missing-value treatment, and preprocessing of the digital indicators are provided in Appendix A.1.

3.2 | Variables and Notation

The dependent variable is y_{it}, the natural logarithm of the numerical value of renewable energy consumption as a percentage of total final energy consumption. The main explanatory variable is the 0–1 composite digitalisation index (DIG) d_{it}. The control vector $\mathbf{x}_{it}$ contains logged GDP per capita, industry value added as a share of GDP, trade as a share of GDP, urban population share, natural-resource rents as a share of GDP, and per-capita CO_2 emissions. Further details on the selection and rationale of the control variables are provided in Appendix A.2. Logarithms are applied to numerical values expressed in the reported units, so their arguments are dimensionless. Core notation is summarised in Table 1, and the index components and entropy weights are reported in Table 2.

TABLE 1 | Model notation and variable definitions.

Symbol	Definition
i	Country index, $i = 1, \ldots, n$
t	Year index, $t = 2010, \ldots, 2022$
j	Digital subindicator index, $j = 1, \ldots, 6$
y_{it}	Logged numerical value of the renewable-energy share
d_{it}	Composite digitalisation index
m_{it}	Logged numerical value of per-capita CO_2 emissions
$\mathbf{x}_{it}$	Column vector of control variables
α_i; τ_t	Country and year fixed effects
ε_{it}	Idiosyncratic disturbance
n; N	Number of countries; number of country-year observations
ρ	Coefficient on the lagged dependent variable in the dynamic-panel model
a; b; c; c'	CO_2-pathway and direct-association coefficients defined in Equations (10–12)
W	Row-standardised four-nearest-neighbour inverse-distance matrix
θ; λ	Spatial contextual coefficient on neighbouring digitalisation; coefficient vector on neighbouring controls
$\bar{y}_t$; d_t; $\bar{X}_t$	Annual cross-sectional means used in the pooled CCE model

3.3 | Index Construction

Let q_{ijt} denote the numerical value of digital subindicator j for country i in year t. Each winsorised benefit indicator is normalised according to Equation (4):

$$z_{ijt} = \frac{q_{ijt}^{W} - q_{j,\min}^{W}}{q_{j,\max}^{W} - q_{j,\min}^{W}}. \tag{4}$$

TABLE 2 | Digitalisation-index components.

Construct	Indicator	Source	Entropy weight
Access	Individuals using the Internet (% of population)	WDI/ITU	6.8%
Access	Fixed broadband subscriptions (per 100 people)	WDI/ITU	15.4%
Access	Mobile cellular subscriptions (per 100 people)	WDI/ITU	4.9%
Secure infrastructure	Secure Internet servers (per 10^6 people)	WDI/Netcraft	45.1%
Productive capability	ICT-service exports (% of service exports)	WDI	13.6%
Productive capability	High-technology exports (% of manufactured exports)	WDI	14.2%

Note: Entropy weights reflect sample dispersion.

For N country-year observations, entropy proportions p_{ijt}, entropy values e_j, and weights w_j are given by Equation (5):

$$p_{ijt} = \frac{z_{ijt}}{\sum_{i,t} z_{ijt}}, e_j = -\frac{1}{\ln N} \sum_{i,t} p_{ijt} \ln p_{ijt}, w_j = \frac{1 - e_j}{\sum_{k=1}^{6} \left(1 - e_k\right)}. \quad (5)$$

The weighted values $v_{ijt} = w_j z_{ijt}$ are compared with the positive and negative ideal solutions v_j^+ and v_j^- using Equation (6):

$$D_{it}^{\pm} = \left[\sum_{j=1}^{6} \left(v_{ijt} - v_j^{\pm} \right)^2 \right]^{1/2}. \quad (6)$$

The digitalisation index is the relative closeness to the positive ideal in Equation (7):

$$d_{it} = \frac{D_{it}^-}{D_{it}^+ + D_{it}^-}. \quad (7)$$

The index ranges from 0 to 1, with larger values indicating stronger national digital-system capacity relative to the pooled sample. Normalisation bounds and entropy weights are calculated from the pooled country-year distribution so that scores remain comparable over time. The main analysis uses the entropy-weighted TOPSIS index, while equal-weight and principal-component indices assess whether the empirical results depend on the weighting rule.

3.4 | Panel Specification and Inference

The primary panel specification is given by Equation (8):

$$y_{it} = \beta d_{it} + \boldsymbol{\gamma}^{\mathrm{T}} \mathbf{x}_{it} + \alpha_i + \tau_t + \varepsilon_{it}. \quad (8)$$

Here, β is the conditional within-country coefficient on digitalisation and $\boldsymbol{\gamma}$ is the coefficient vector for the controls. Country effects α_i remove time-invariant national components, while year effects τ_t absorb shocks shared across countries, including global technology diffusion, commodity-price changes, and international climate-policy developments. Because both digitalisation and renewable-energy use trend over time, this specification provides the more stringent within-country comparison.

Country-only fixed effects are retained to show how estimates change when common time movement is not absorbed. Random effects are reported as an additional model but require stronger orthogonality assumptions. The supplied diagnostics report cross-sectional dependence, serial correlation, and groupwise heteroskedasticity. We therefore compare country-clustered, two-way-clustered, and Driscoll–Kraay inference where the exact specification is reproducible. Robust standard errors address uncertainty.

3.5 | Dynamic-Panel Sensitivity

Dynamic-panel sensitivity models estimate Equation (9):

$$y_{it} = \rho y_{i,t-1} + \beta d_{it} + \boldsymbol{\gamma}^{\mathrm{T}} \mathbf{x}_{it} + \alpha_i + \tau_t + \varepsilon_{it}. \quad (9)$$

The preferred Difference GMM specification treats $y_{i,t-1}$ and d_{it} as endogenous, uses their second and third lags as instruments, and treats $\mathbf{x}_{it}$ as conditionally exogenous. Instruments are collapsed and restricted to 21, well below the 156 country groups. Estimation uses two-step GMM with Windmeijer-corrected standard errors. A predetermined-digitalisation specification and a restricted System GMM model provide complementary checks under alternative timing and moment conditions.

3.6 | CO2 Pathway Decomposition

The CO_2 pathway decomposition estimates Equations (10–12):

$$y_{it} = c\, d_{it} + \boldsymbol{\delta}^{\mathrm{T}} \mathbf{x}_{it}^{(-m)} + \alpha_i^{(y)} + \tau_t^{(y)} + u_{it}, \quad (10)$$

$$m_{it} = a\, d_{it} + \boldsymbol{\theta}^{\mathrm{T}} \mathbf{x}_{it}^{(-m)} + \alpha_i^{(m)} + \tau_t^{(m)} + v_{it}, \quad (11)$$

$$y_{it} = c'\, d_{it} + b\, m_{it} + \boldsymbol{\kappa}^{\mathrm{T}} \mathbf{x}_{it}^{(-m)} + \tilde{\alpha}_i^{(y)} + \tilde{\tau}_t^{(y)} + \eta_{it}. \quad (12)$$

Here, $\mathbf{x}_{it}^{(-m)}$ excludes logged per-capita CO_2 emissions. The pathway associated with CO_2 is measured by the coefficient product ab, and the remaining digitalisation coefficient is c'. Statistical significance of ab is evaluated with 2000 country-block bootstrap replications, which preserve within-country dependence. Both country fixed-effects and country-and-year fixed-effects specifications are estimated to assess the contribution of common time shocks.

The coefficient product quantifies the part of the digitalisation–renewable-energy association that operates statistically through the CO_2 equation. Because the variables are observed contemporaneously, the result is interpreted as a CO_2-related pathway rather than a time-ordered causal mechanism.

3.7 | Heterogeneity

Emissions moderation is tested in two country-and-year fixed-effects models. The first interacts digitalisation with mean-centred logged per-capita CO_2 emissions. The second interacts digitalisation with an indicator for countries above the median of country-average emissions. Income heterogeneity is assessed with a continuous interaction between digitalisation and mean-centred logged GDP per capita and with interactions for three equally sized groups based on country-average logged GDP per capita. Group-specific slopes and their pairwise differences are calculated from the same full-sample model, and Wald tests evaluate whether the slopes are jointly equal.

3.8 | Common Factors and Geographic Spillovers

The Pesaran CD test indicates cross-sectional dependence, which can arise when countries respond to shared technology, price, financial, or policy shocks. We therefore estimate a pooled common-correlated-effects (CCE) model. The country fixed-effects specification is augmented with annual cross-sectional means of the outcome, digitalisation, and the controls. This specification is written as Equation (13).

$$y_{it} = \beta d_{it} + \boldsymbol{\gamma}^{\mathrm{T}}\mathbf{x}_{it} + \pi_y \overline{y}_t + \pi_d \overline{d}_t + \boldsymbol{\Pi}_x^{\mathrm{T}}\overline{\mathbf{x}}_t + \alpha_i + \varepsilon_{it}. \tag{13}$$

The cross-sectional means proxy the influence of unobserved common factors without requiring their number to be specified in advance (Pesaran 2006). Comparing CCE with the country and year fixed-effects estimate shows whether the digitalisation coefficient is sensitive to alternative treatments of common international variation.

Geographic spillovers are estimated with a spatial-lag-of-X (SLX) model. The SLX specification is given by Equation (14).

$$y_{it} = \beta d_{it} + \theta (Wd)_{it} + \boldsymbol{\gamma}^{\mathrm{T}}\mathbf{x}_{it} + \boldsymbol{\lambda}^{\mathrm{T}}(W\mathbf{x})_{it} + \alpha_i + \tau_t + \varepsilon_{it}. \tag{14}$$

The row-standardised matrix W assigns inverse-distance weights to each country's four nearest neighbours using World Bank country coordinates. The coefficient β captures the own-country association, while θ measures whether neighbouring countries' digital capacity is associated with the domestic renewable-energy share after accounting for country and year effects. The SLX form is appropriate for testing contextual exposure through observed neighbouring characteristics and avoids imposing feedback through a spatially lagged dependent variable.

4 | Results

4.1 | Descriptive Statistics and Identifying Variation

The within-country standard deviation of the digitalisation index is 0.122, compared with a total standard deviation of 0.198. Considerable within-country variation remains, but year effects remove changes shared across countries. This distinction is important because the principal estimate changes substantially when year effects are included. Descriptive statistics are reported in Table 3; the geographic distribution and correlation structure are shown in Figures 2 and 3, respectively.

TABLE 3 | Descriptive statistics reproduced from the supplied panel.

Variable	*N*	Mean	SD	Min	Max
ln renewable-energy share	1875	2.636	1.929	−4.605	4.575
Composite digitalisation index	1875	0.228	0.198	0.016	0.929
ln GDP per capita	1875	8.810	1.435	5.934	11.682
ln industry value added	1875	3.173	0.438	0.872	4.342
ln trade openness	1875	4.351	0.532	1.418	6.093
ln urban population share	1875	4.029	0.441	2.758	4.605
ln natural-resource rents	1875	0.237	2.225	−4.605	4.140
ln CO_2 emissions per capita	1875	0.873	1.374	−3.087	3.982

4.2 | Baseline Estimates

The country fixed-effects coefficient implies that a 0.1-point increase in the digitalisation index is associated with 100[exp $(0.1 \times 0.3830) - 1] = 3.9\%$ higher renewable-energy share. For a country with a renewable share of 20%, this relative change corresponds to an increase to approximately 20.78%, or 0.78 percentage points. Under country and year fixed effects, the corresponding estimate is about 1.0%; at the same 20% baseline, this equals an increase to approximately 20.20%, or 0.20 percentage points. The complete set of baseline estimates is reported in Table 4.

The baseline country fixed-effects estimate is positive and statistically significant. Its reduction from 0.3830 to 0.0995 after year effects are included shows that shared international change is an important component of the observed relationship. The positive association is therefore strongest when both national digital development and common global diffusion are retained, while the country-specific component is smaller. H1 is supported by the baseline model, with the estimated magnitude varying across the treatment of common time variation.

4.3 | Sensitivity Analyses

We estimate each feasible sensitivity model with both country and year fixed effects and country-clustered standard errors. An equal-weight index using pooled 5%–95% winsorisation and pooled min–max normalisation is also constructed. The PCA index is constructed usingpooled z-score standardisation of the six indicators, extraction of the first principal component, and pooled min–max rescaling. The index excluding secure servers is constructed analogously using the remaining five indicators. The results are summarised in Table 5.

The CCE estimate is nearly identical to the TWFE estimate, confirming that the country-specific coefficient remains small when common factors are represented by cross-sectional averages. In the spatial SLX model, both the own-country and neighbouring-country point estimates are positive, although neither reaches conventional significance. Together, these

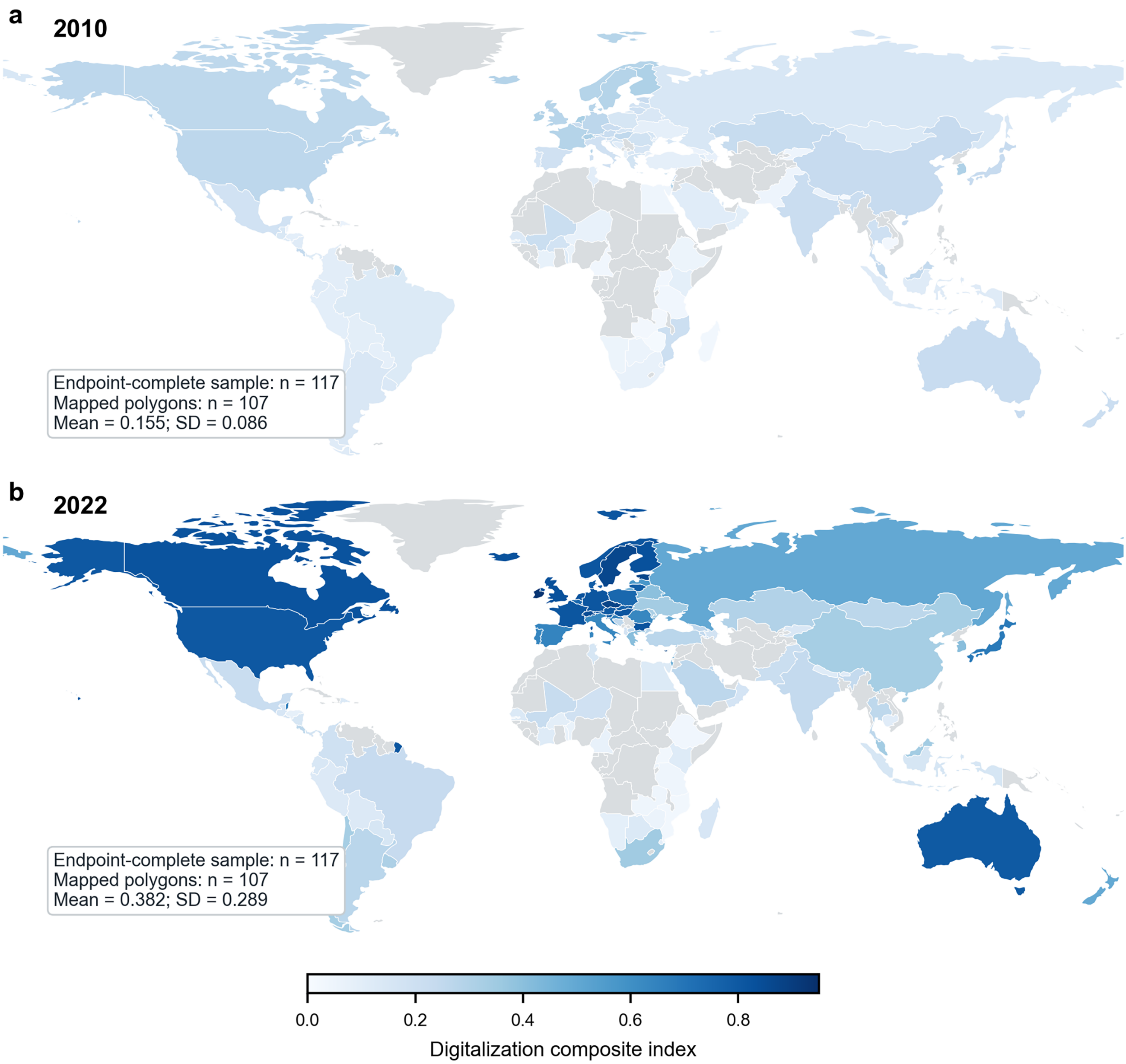

FIGURE 2 | Global distribution of the digitalisation composite index in 2010 and 2022. The estimation sample contains 156 countries; grey areas indicate missing values or territories not covered by the basemap. The maps compare the same 117 countries with observations in both years. Of these, 107 are represented by separate basemap polygons; 10 small states or territories are not separately displayed. Summary refer to all 117 countries.

results identify a substantial common international component and a positive but statistically uncertain geographic component.

We additionally vary the collapsed Difference GMM instrument window. Digitalisation coefficients are −0.4646 (SE 0.4739) with lag 2 only, −0.6599 (SE 0.3511) with lags 2–3, and −0.6856 (SE 0.2396) with lags 2–4. Instrument counts range from 19 to 23. AR(2) p-values range from 0.099 to 0.263; Hansen p-values are 0.197 and 0.430 in the overidentified models. The coefficient remains negative across all three windows and becomes more precisely estimated as the lag window expands. The dynamic-panel results therefore reveal a different short-run pattern from the positive static country fixed-effects estimate and reinforce the importance of model timing.

4.4 | CO2 Pathway Decomposition

The country fixed-effects equations yield a total digitalisation coefficient of 0.6144 when CO_2 is omitted. Digitalisation is negatively associated with per-capita CO_2 emissions (path a = −0.4221), and per-capita CO_2 emissions are negatively associated with the renewable-energy share conditional on digitalisation (path b = −0.5482). After CO_2 is included, the direct digitalisation coefficient is 0.3830. The coefficient signs define a positive pathway: stronger digital capacity is associated with lower emissions, and lower emissions are associated with a higher renewable-energy share.

The product ab equals 0.2314 under country fixed effects, with a bootstrap standard error of 0.0539 and a 95% percentile interval

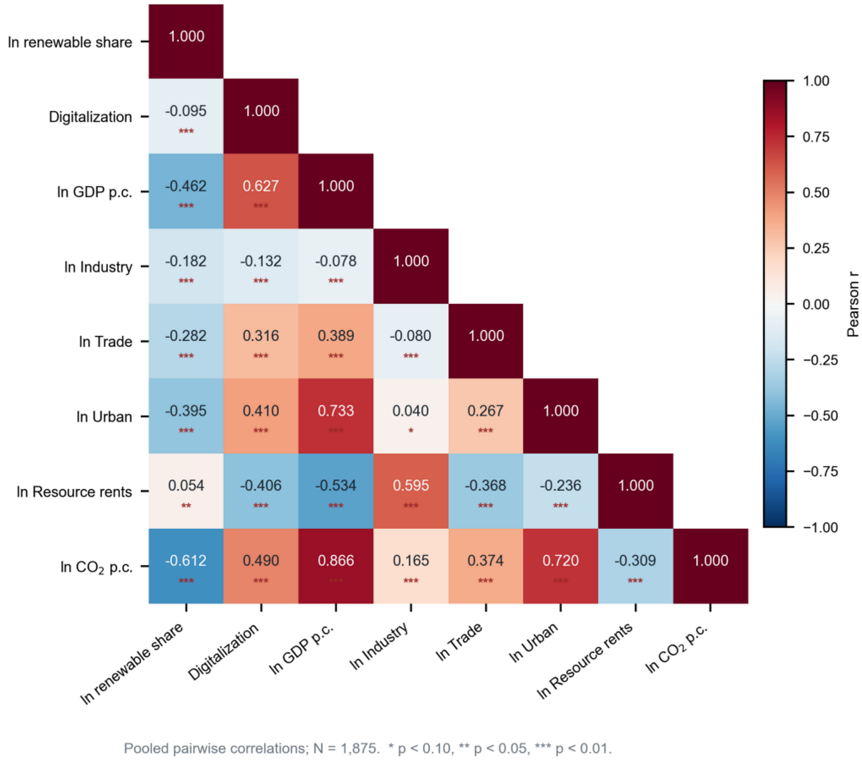

FIGURE 3 | Pearson correlation matrix of the main variables. Correlations and significance levels are computed from the complete analytical sample of 1875 country-year observations.

TABLE 4 | Association between digitalisation and the renewable-energy share.

Specification	Coefficient on DIG	SE	p	N	Interpretation
Country FE; country-clustered	0.3830	0.0893	< 0.001	1875	Positive within-country association without controlling for common year shocks
Country and year FE; country-clustered	0.0995	0.1298	0.4432	1875	Smaller, imprecise estimate after common shocks
Country and year FE; Driscoll–Kraay, bandwidth 3	0.0995	0.0643	0.1220	1875	Same point estimate; still imprecise at 5%
Random effects; country-clustered	0.3377	0.0746	< 0.001	1875	Positive under stronger RE assumptions
Difference GMM; endogenous DIG, lags 2–3	−0.6599	0.3511	0.0602	1563	Two-step, Windmeijer-corrected; 21 collapsed instruments
System GMM; endogenous DIG, lags 2–3	−0.1660	0.3562	0.6411	1563	Two-step, Windmeijer-corrected; 24 collapsed instruments

Note: All models include the listed controls. The GMM models also include a lagged dependent variable and year indicators. For Difference GMM, AR(1) $z = -1.70$ ($p = 0.089$), AR(2) $z = 1.12$ ($p = 0.263$), and Hansen $\chi^2(2) = 3.25$ ($p = 0.197$). The lack of conventional AR(1) rejection limits diagnostic reassurance. The corresponding System GMM diagnostics are AR(1) $p = 0.072$, AR(2) $p = 0.205$, and Hansen $p = 0.378$.

TABLE 5 | Sensitivity analyses.

Sensitivity	Coefficient	SE	p	N	Evidentiary status
One-year lag of DIG	0.0902	0.1294	0.4863	1719	Imprecise with year effects
Exclude countries with mean renewable share > 80%	0.0871	0.1368	0.5244	1718	Similar to primary estimate
PCA alternative index	−0.2992	0.2742	0.2753	1874	Scale differs from TOPSIS
Five-indicator PCA excluding secure servers	−0.6066	0.3134	0.0531	1874	Borderline negative estimate
Equal-weight index	−0.0811	0.2608	0.7558	1874	Imprecise
Pooled common correlated effects	0.0999	0.1240	0.4206	1875	Imprecise after common-factor proxies
Spatial SLX: own DIG	0.0712	0.1256	0.5708	1875	Imprecise direct contextual association
Spatial SLX: neighbouring DIG	0.1030	0.1639	0.5299	1875	No precise geographic spillover evidence

Note: All models use country and year fixed effects except pooled CCE, which uses cross-sectional averages to represent common factors. Because the TOPSIS, PCA, and equal-weight indices have different empirical scales, their estimates are compared by direction, precision, and substantive pattern. In the quadratic TWFE model, the linear and squared terms are jointly insignificant (Wald $p = 0.438$).

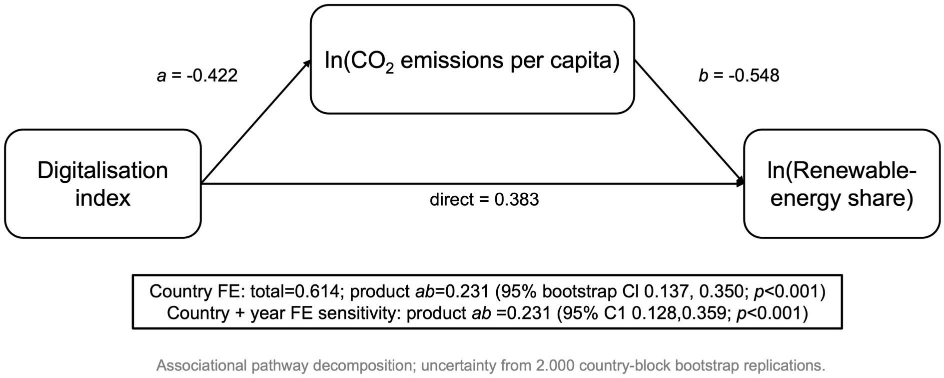

FIGURE 4 | CO_2 pathway decomposition. Path coefficients are estimated from country fixed-effects equations. Product-term uncertainty is based on 2000 country-block bootstrap replications. The country-and-year fixed-effects product is reported as a sensitivity estimate.

TABLE 6 | Formal moderation tests.

Moderation test	Estimate	SE	p	Interpretation
DIG × continuous ln CO_2	0.2027	0.1085	0.0620	Positive but imprecise at 5%
High-CO_2 minus low-CO_2 slope	0.5183	0.2133	0.0152	Larger slope above country-median emissions
DIG × continuous ln GDP per capita	0.1539	0.0862	0.0744	Weak positive gradient
Middle-income-tercile minus low-tercile slope	−0.4838	0.4440	0.2760	Imprecise difference
High-income-tercile minus low-tercile slope	0.0208	0.4316	0.9616	No difference
High-income-tercile minus middle-tercile slope	0.5046	0.1837	0.0060	Positive formal contrast

Note: All estimates come from unified country-and-year fixed-effects models with country-clustered standard errors. The three income-tercile slopes are jointly unequal (Wald $p = 0.0216$). Income terciles contain 52 countries each and are based on country-average logged GDP per capita.

of [0.1368, 0.3496]. The interval excludes zero, and none of the 2000 country-block bootstrap products is non-positive (two-sided bootstrap $p < 0.001$). The CO_2-related pathway is therefore positive and statistically significant. It represents 37.7% of the total country fixed-effects association ($ab/c = 0.2314/0.6144$).

The result is highly similar after adding year fixed effects. The product is 0.2310 (bootstrap SE 0.0582; 95% interval [0.1276, 0.3590]; $p < 0.001$), representing 69.9% of the corresponding total association. These estimates support H2 by identifying a statistically significant CO_2-related pathway linking digitalisation and the renewable-energy share. The pathway is interpreted as a contemporaneous decomposition because the annual panel does not establish the temporal sequence among the three variables. The pathway estimates are visualised in Figure 4.

4.5 | Heterogeneity

The moderation tests identify meaningful variation across national contexts. The continuous emissions interaction is positive at the 10% level, and the high-versus-low emissions contrast is positive and statistically significant at the 5% level. Income slopes are also jointly different (Wald $p = 0.0216$): the estimated slopes are 0.1473, −0.3365, and 0.1681 in the low-, middle-, and high-income terciles. The pattern is U-shaped rather than monotonic, with a significant difference between the high- and middle-income groups. These results support H3 by showing that per-capita emissions levels and development context alter the digitalisation–renewable-energy relationship. Formal moderation estimates are reported in Table 6, and the main contextual contrasts are summarised in Figure 5.

5 | Discussion

5.1 | Central Finding

The central finding is a positive relationship between national digital-system capacity and the renewable-energy share. Under country fixed effects, a 0.1-point increase in the digitalisation index is associated with a 3.9% increase in the renewable share. The smaller TWFE and pooled CCE coefficients further show that this relationship contains an important international component: digital and renewable technologies have diffused across countries through common costs, standards, policies, and investment flows. Digitalisation is therefore connected to the renewable-energy transition through both national development and shared global change.

This finding is consistent with the broad direction of earlier cross-country evidence. Shahbaz et al. (2022) report a positive digital-economy relationship with renewable-energy consumption and generation across 72 countries, with governance playing an important role. Lee et al. (2023) identify positive ICT associations that vary across the renewable-energy distribution and country-risk conditions. Fambeu and Yomi (2024) show that economic growth and structural transformation shape the

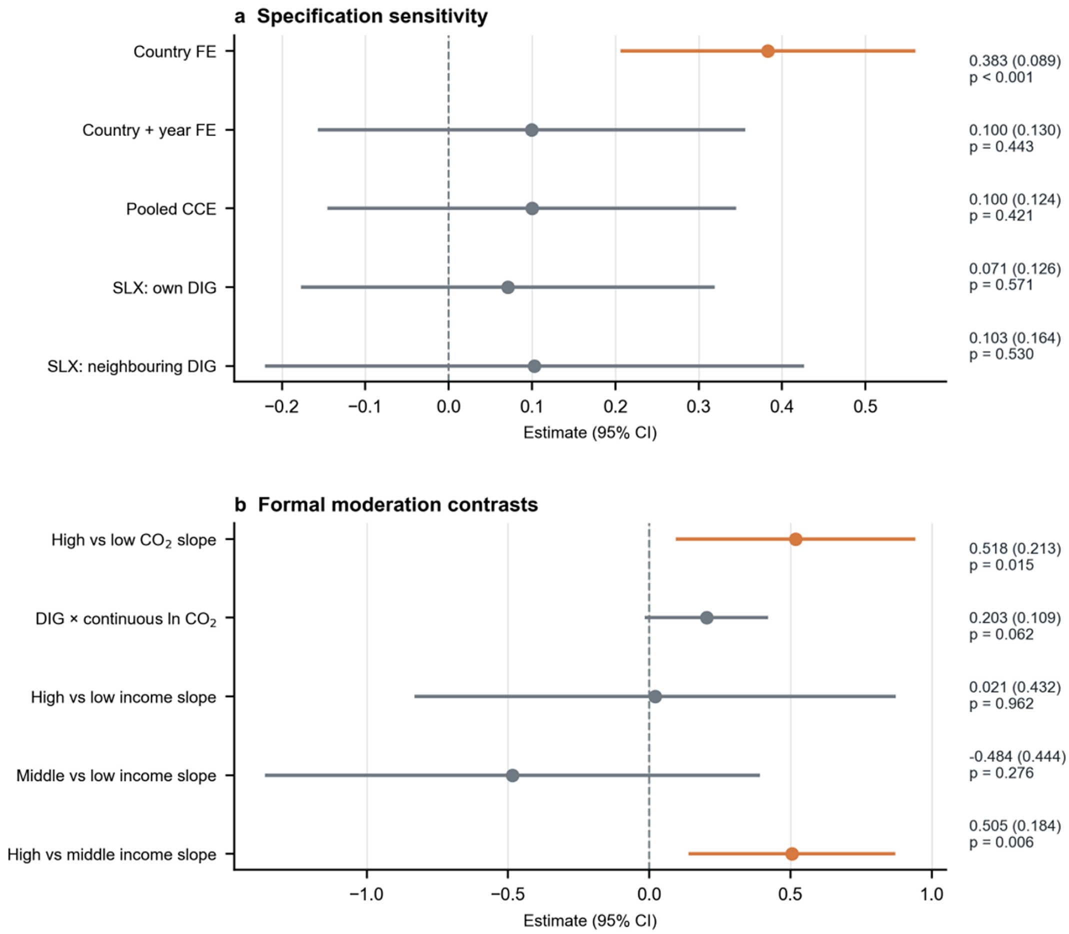

FIGURE 5 | Digitalisation estimates and contextual contrasts. Panel a compares estimates under country fixed effects, country-and-year fixed effects, pooled common correlated effects, and the spatial-lag-of-X specification. Panel b reports formal interaction or cross-group slope contrasts from unified country-and-year fixed-effects models. Horizontal bars are 95% confidence intervals; standard errors are clustered by country.

relationship in Africa. By using the renewable share of total final consumption, the present study extends this evidence beyond electricity generation to an economy-wide consumption measure.

The comparison across country FE, TWFE, and CCE makes a second contribution. Earlier positive estimates can reflect two substantive processes: improvements within individual countries and international changes that raise digitalisation and renewable use together. The similarity between the TWFE coefficient (0.0995) and CCE coefficient (0.0999) shows that the common international component is quantitatively important. Separating national and global variation clarifies why estimates differ across panel specifications and identifies international diffusion as a substantive part of the relationship.

The moderation results add a third contribution by identifying where the relationship is strongest. The digitalisation slope is significantly larger in high-emissions settings, and income slopes differ jointly across terciles. Zheng and Zhang (2025) also report stronger estimates in high-income, OECD, and financially developed countries, while Hwang and Venter (2025) identify variation associated with fossil-fuel dependence. The present results show that national context matters, but in a non-monotonic form: per-capita emissions levels produce the clearest gradient, whereas income combines infrastructure maturity, institutional capacity, fossil lock-in, and digital demand.

5.2 | Mechanisms and Competing Explanations

The positive baseline association can first be explained by improvements in energy-system operation. Digital sensors, smart metres, forecasting algorithms, and automated control increase the visibility of generation and demand. Better forecasts reduce balancing errors for wind and solar power, while real-time monitoring and predictive maintenance can shorten outages and improve asset use (Ahmad et al. 2021; IEA 2017). Digital platforms also facilitate demand response and the coordination of distributed generation, storage, and prosumers. These operational channels are directly relevant to the renewable share because they increase the amount of variable renewable energy that an existing system can accommodate.

A second mechanism operates through investment and market coordination. Digital records and communication reduce information and transaction costs between generators, grid operators, regulators, financiers, and consumers. Their value, however, depends on complementary institutions and physical infrastructure. Governance quality shapes whether information supports credible implementation, while financial development affects whether digital capability is converted into renewable investment (Hadj et al. 2025; Hwang and Venter 2025; Shahbaz et al. 2022). This complementarity helps explain the significant emissions and income interactions: countries with greater substitution pressure or stronger implementation capacity can obtain larger energy-transition benefits from comparable digital resources.

The attenuation between country fixed effects and TWFE/CCE also points to an international diffusion mechanism. Declining costs of digital and renewable technologies, common technical standards, cross-border learning, climate-policy diffusion, and international finance can raise both variables across many countries. Country fixed effects retain this shared movement, whereas year effects and common-factor proxies remove much of it. The smaller TWFE and CCE coefficients therefore show that global diffusion is an important part of the observed digitalisation–renewable-energy connection, alongside country-specific change.

Digitalisation can also create offsetting pressure. Data centres, telecommunications networks, and computing equipment increase electricity and material demand, and efficiency improvements may induce rebound effects (Briglauer et al. 2023; de Vries 2023). Cybersecurity risks and uneven access may further limit system-wide benefits (Kim et al. 2026). The estimated coefficient consequently reflects the balance between operational and coordination gains on one side and the energy footprint of digital expansion on the other. This balance provides a concrete explanation for the heterogeneous estimates across national contexts.

5.3 | The Role of CO_2 Emissions

The CO_2 results reveal two distinct features of the digitalisation–renewable-energy relationship. First, emissions condition the size of the digitalisation coefficient. The positive continuous interaction (0.2027, $p = 0.062$) and the significant high-versus-low emissions contrast (0.5183, $p = 0.015$) show that digitalisation is more strongly associated with renewable energy in carbon-intensive settings. These countries have greater scope for fuel substitution and often face stronger pressure to modernise energy systems, so digital coordination can yield larger changes in renewable use.

Second, CO_2 emissions form a statistically significant pathway between digitalisation and the renewable-energy share. Digitalisation is associated with lower per-capita emissions ($a = -0.4221$), while lower emissions are associated with a higher renewable share ($b = -0.5482$). Their positive product is 0.2314 under country fixed effects and remains 0.2310 after year effects are added; both bootstrap tests give $p < 0.001$. This result is consistent with research linking digital development to energy efficiency, green-technology diffusion (Alfalih and Hadj 2026; Zhao et al. 2024), industrial upgrading, and lower emission intensity (Chen et al. 2023; Jahanger et al. 2026; Zhou et al. 2024).

Moderation and pathway decomposition answer complementary questions. The interaction results identify where the digitalisation association is stronger, while the product term identifies how much of the estimated relationship coincides with the CO_2 equation. Under country fixed effects, the CO_2 pathway accounts for 37.7% of the total association. Its persistence after year effects indicates that the pathway is not driven solely by common global trends. Because all three variables are annual and contemporaneous, the decomposition does not establish whether emissions decline precedes renewable substitution; longitudinal mediation with explicit lags would be required to determine that sequence (Imai et al. 2010).

5.4 | Boundary Conditions and Theoretical Implications

The heterogeneity results define the settings in which digitalisation is most strongly connected to renewable-energy use. The high-emissions contrast is positive and significant, consistent with greater substitution opportunities in carbon-intensive systems. Income differences are also statistically meaningful, but they are not linear. The middle-income slope is lower than both the low- and high-income slopes, suggesting that development level combines several countervailing forces rather than operating as a simple resource gradient.

In lower-income countries, improvements in connectivity and basic digital management can relax binding information and coordination constraints, although limited finance and grid capacity may restrict implementation. Middle-income economies may combine rapid digital demand growth with incomplete grid modernisation and continued fossil-fuel dependence. High-income economies benefit from mature infrastructure and institutions, but basic connectivity may already be saturated. The observed U-shaped pattern is compatible with these differing combinations of opportunity, capacity, and digital energy demand.

These results extend general-purpose technology and ecological modernisation arguments. Digital technologies create value through complementary organisational and infrastructural change rather than through connectivity alone (Bresnahan and Trajtenberg 1995; Mol and Spaargaren 2000). The significant contextual differences provide empirical support for this complementarity perspective: the same level of national digital capacity is associated with different renewable-energy outcomes depending on per-capita emissions level and development conditions. Digitalisation should therefore be understood as an enabling system whose energy-transition value is realised through grids, institutions, skills, finance, and environmental policy.

5.5 | Limitations and Future Research

Three limitations define the scope of the findings. First, the composite index measures national digital-system capacity rather than direct adoption in the energy sector; future data on smart metres, grid automation, energy-data platforms, and firm-level technologies would identify the operational channels more closely. Second, the observational panel supports cross-country associations but does not provide an external source of quasi-experimental variation. Third, the renewable share of final consumption captures one central dimension of transition, while the single four-neighbour spatial matrix cannot represent every trade, finance, policy, or network connection.

Future research can address these limits by combining sector-specific digital indicators with longer panels, alternative economic and network weight matrices, and research designs that establish temporal order.

6 | Conclusions and Policy Implications

6.1 | Conclusions

Using an unbalanced panel of 156 countries from 2010 to 2022, this study shows that national digital-system capacity is positively associated with the renewable-energy share. In the country fixed-effects model, a 0.1-point increase in the digitalisation index corresponds to a 3.9% increase in the renewable share. The coefficient becomes smaller after common time shocks and common-factor proxies are introduced, demonstrating that international digital and renewable diffusion constitutes an important part of the relationship.

The analysis also identifies two substantive sources of variation. The CO_2-related product is positive and statistically significant under both country fixed effects and country-and-year fixed effects ($p < 0.001$), accounting for 37.7% of the total country fixed-effects association. In addition, formal interaction tests show stronger digitalisation slopes in high-emissions settings and significant, non-monotonic differences across income groups. These findings establish digitalisation as an important enabling capacity whose association with renewable-energy use depends on common global change and national conditions.

6.2 | Policy Implications

Governments should connect digital investment to the operational requirements of renewable-energy integration. Broadband expansion alone is insufficient. Priority applications include smart metering, renewable-generation forecasting, interoperable grid data, automated dispatch, predictive maintenance, demand response, and transparent connection procedures. Digital and physical infrastructure should be planned together so that networks, storage, transmission, and skilled personnel can convert better information into renewable-energy use.

Policy design should also reflect national conditions. Carbon-intensive systems can use digital monitoring, dispatch, and planning to accelerate substitution where the estimated association is strongest. Lower-income countries may obtain large gains from closing basic connectivity and grid-management gaps, but finance and institutional capacity remain essential. Middle-income countries require particular attention to fossil-fuel lock-in and the rapid growth of digital electricity demand, while high-income countries should emphasise interoperability, flexible demand, and advanced system optimisation.

Finally, the environmental footprint of digitalisation should be governed directly. Clean-electricity procurement and efficiency standards for data centres and networks, cybersecurity requirements, equipment-lifetime standards, and electronic-waste management can preserve the energy-system benefits of digital expansion. Coordinating these measures with renewable-energy policy will allow digital infrastructure to function as part of the transition rather than as a separate technology programme.

Author Contributions

Lianghan Cong: conceptualization, methodology, data curation, writing – original draft. **Shuaiyi Lu:** data curation, writing – review and editing. **Pan Jiang:** methodology, writing – review and editing. **Xiaoshu Lü:** funding acquisition, writing – review and editing, supervision.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data used in this study are publicly available from the World Bank World Development Indicators (WDI). The telecommunications indicators included in the digitalisation index are originally compiled by the International Telecommunication Union (ITU) and accessed through the WDI database. The processed panel dataset and constructed digitalisation indices used in the analysis are available from the corresponding author upon reasonable request.

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Appendix A: Additional Variable and Preprocessing Details

Detailed Sample Construction and Preprocessing

The initial panel contains 1927 observations for 160 codes over 2010–2022. AFE and SST are excluded because they are World Bank aggregates rather than countries. Complete-case selection across the outcome, digitalisation index, controls, and per-capita CO_2 emissions leaves 1875 observations for 156 countries. Montenegro and Palestine are excluded because their CO_2 series are entirely missing. The retained country histories range from 4 to 13 years.

For a generic scalar value s, variables that can take zero values, including the renewable-energy share, natural-resource rents, and per-capita CO_2 emissions, are transformed as $\ln(s + 0.01)$; strictly positive controls use $\ln(s)$. Internal gaps are filled by within-country linear interpolation, and the nearest observed value is used at series boundaries. The six digital indicators are winsorised at the pooled 5th and 95th percentiles before pooled min–max normalisation and entropy-weighted TOPSIS aggregation. These pooled rules apply a common scale and weighting benchmark across all country-years.

Control-Variable Rationale

Following the relevant literature in energy economics, this paper includes the following control variables. First, the natural logarithm of GDP per capita, denoted by $\ln(PGDP)$, is used to control for the level of economic development. Higher income usually implies stronger capacity for green investment and technology absorption, although its specific effect may also depend on consumption patterns and industrial structure (Smeets Křístková et al. 2025). Second, the natural logarithm of industrialisation rate, denoted by $\ln(IND)$, is used to control for industrial structure. Countries with a larger industrial share tend to rely more heavily on conventional energy, which may inhibit the increase in the renewable energy share (Zirui et al. 2025). Third, the natural logarithm of trade openness, denoted by $\ln(TRADE)$, reflects the degree of integration into the global market and may improve energy transition through technology diffusion and equipment imports (Mai et al. 2025). Fourth, the natural logarithm of urbanisation rate, denoted by $\ln(URB)$, is used to control for spatial population concentration and changes in energy consumption patterns (Chen and Lubabu 2026). Fifth, the natural logarithm of natural resource rents as a share of GDP, denoted by $\ln(RENT)$, is used to measure resource dependence. Countries with stronger resource dependence are more likely to experience fossil fuel path dependence (Sun and Qamruzzaman 2025). Sixth, the natural logarithm of per capita CO_2 emissions, denoted by $\ln(CO_2)$, is included as a control variable in the baseline model and as an intermediate variable in the exploratory decomposition.