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THE ROLE OF GOVERNMENT AI READINESS IN SHAPING RENEWABLE ELECTRICITY CAPACITY AND OUTPUT

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Abstract: *The accelerating energy transition increasingly depends on human–AI interaction in government, how public agencies, regulators, and system operators use AI to plan, permit, and manage renewable integration while maintaining reliability. This study examines whether Government AI Readiness is associated with renewable electricity development, distinguishing between installed capacity and total generation. An unbalanced panel of 179–183 countries (2020–2024) combines Government AI Readiness Index scores with renewable capacity and generation data and GDP per capita (IRENA/World Bank), analysed using transformed variables, diagnostics, and fixed/random effects panel models in R. Government AI Readiness is positively and significantly linked to total installed renewable capacity; in the FE model, a one-point increase in AI readiness is associated with ~0.017 higher log installed capacity ($p < 0.001$). No significant association is found for total renewable generation, implying that AI-ready governance may accelerate infrastructure rollout without automatically increasing output due to operational, infrastructural, or climatic constraints.*

Keywords: *artificial intelligence, government AI readiness, energy transition, renewable electricity capacity, renewable electricity generation, panel data analysis.*

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INTRODUCTION

Governments worldwide are rapidly expanding investments in renewable energy to meet ambitious climate goals. According to the International Energy Agency, global renewable energy installations broke records in 2024 – adding around 700 GW, with renewables accounting for 38% of global energy supply growth (IRENA, 2025). However, IRENA (2025) underscores that this pace falls short of what is needed; to triple global renewable capacity by 2030 in alignment with the 1.5 °C pathway, renewables must grow at an annual rate of 16.6 %, far exceeding current trends. At the same time, the IEA's flagship Energy and AI report reveals that AI not only increases electricity demand, particularly via energy-intensive data centres, but also holds strong potential to optimise energy systems, enhance grid capacity, and improve cost-efficiency via data-driven deployment and operations.

AI has emerged as a strategic enabler for renewable energy deployment and integration. The IRENA (2019) identifies AI and big data among the six principal categories of innovation needed to integrate variable renewable energy into power systems. These technologies improve forecasting accuracy, enable real-time grid optimisation, and support predictive maintenance, ultimately enhancing system flexibility, reducing operational disruptions, and improving the efficiency of renewable energy installations.

Moreover, the World Bank (2025) underscores how digital transformation, including AI, can modernise energy infrastructure and help scale up renewable energy deployment. Their energy overview highlights that AI-powered digital tools, such as those for grid management and demand forecasting, are critical for increasing system efficiency and reducing energy losses, supporting the broader adoption of clean energy sources. By combining technological readiness with structural energy transition strategies, these developments position AI as a linchpin in overcoming key operational and infrastructural challenges in the shift to clean electricity.

In this context, understanding the *role of government AI readiness* in facilitating renewable energy development is more relevant than ever. AI readiness reflects a government's capacity to harness digital infrastructure, governance frameworks, and human capital to support innovation in the energy sector. While agencies like the IEA spotlight the AI–energy nexus, and policy memos such as those by the U.S. Department of Energy outline AI's deployment opportunities in planning and grid management (UNESCO, n.d.), systematic empirical evidence on how government AI capabilities translate into renewable energy installation and generation remains sparse. This gap underscores the urgency of exploring whether AI preparedness is a meaningful enabler of renewable energy transitions, which is precisely the focus of this study.

Renewable electricity capacity expansion and output growth increasingly depend not only on resource endowments and market incentives, but also on a country's ability to plan, regulate, finance, and digitally operate complex energy systems. This shifts attention towards "government AI readiness" as a public-sector capability that can accelerate renewable deployment through better forecasting, permitting, grid management, risk oversight, and the quality of public services supporting the energy transition (Androniceanu, 2024; Murko et al., 2024). Government AI readiness is also intertwined with broader governance quality and integrity, because the benefits of digital decision-support tools depend on transparency, accountability, and bias control in public administration (Pollifroni et al., 2025; Yefimenko et al., 2025a). At the macro level, readiness can affect economic confidence and investment conditions by strengthening state capacity to manage shocks and coordinate infrastructure programmes, which is relevant in turbulent periods when energy markets and inflation pressures co-move (Senci & Afful, 2025; Wołowiec et al., 2022).

The research landscape therefore suggests a plausible "public capability channel": higher government AI readiness supports faster renewable electricity capacity growth and more stable renewable output by improving policy execution, market coordination, and operational efficiency across the electricity value chain. This channel is consistent with the expansion of digital governance models and AI-enabled public management, where administrative performance and socio-economic welfare outcomes increasingly reflect digital maturity and institutional design (Androniceanu, 2024; Murko et al., 2024). At the same time, this landscape also highlights constraints, ethical safeguards, skills, organisational adoption, and the political economy of reforms, without which AI readiness may remain symbolic rather than productive for the energy transition (Mujtaba, 2025; Mura & Stehlíková, 2025).

Defining the capability base: governance, ethics, skills, and adoption as prerequisites

A first cluster of studies frames AI readiness as a governance and institutional capacity issue rather than a purely technological one. Public administration perspectives emphasise that generative AI and automation reshape public-sector processes, but the realised value depends on how governments design rules, oversight, and service delivery models (Androniceanu, 2024; Murko et al., 2024). Because electricity transitions rely on long-horizon planning and high-trust regulation, ethical governance becomes directly relevant: AI systems can amplify opacity, bias, and unequal access if safeguards are weak, which may undermine public acceptance of energy reforms and infrastructure decisions (Haley, 2025; Mujtaba, 2025). The literature further stresses the need to protect human dignity and social justice while also considering environmental stability when scaling AI in governance and the economy, implying that "readiness" should include normative and regulatory maturity, not only technical infrastructure (Mura & Stehlíková, 2025).

A second enabling dimension is human capital and organisational adoption. Evidence on intention to use AI and the competence structure of effective AI use indicates that readiness is shaped by skills, perceived usefulness, and organisational conditions, factors that matter in public utilities, regulators, and state-owned network operators as much as in private firms (Alhammadi, 2025; Popa et al., 2024). Related work shows that technological competence can moderate sustainability-oriented HRM effectiveness when AI is embedded into management systems, suggesting that capability complements (skills, processes, and culture) condition the transition benefits of digital tools (Abid et al., 2024). This adoption lens is reinforced by research on AI in project management, where bibliometric mapping implies a growing emphasis on how AI changes planning, coordination, and delivery, precisely the domains critical for renewable energy programmes and grid investments (Ibadildin et al., 2025).

A third prerequisite concerns integrity and trust. Awareness of unethical AI and mitigation measures points to the practical need for risk identification, standards, and training to prevent harmful or unreliable AI use (Höller et al., 2023). Broader societal attitudes (ranging from fear to hope) also shape how technology-led reforms are received, which can indirectly influence the political feasibility of renewable energy expansion and the acceptance of operational digitalisation (Yarovenko et al., 2024). In education and research systems, the relationship between AI, integrity, and capability building is likewise highlighted as a condition for sustainable skill pipelines and trustworthy innovation ecosystems (Artyukhov et al., 2024b).

Linking AI readiness to the macro investment environment and sustainable finance for renewables

Renewable electricity capacity is capital intensive, so the literature on digitalisation, sustainable finance, and ESG performance provides an important bridge between AI readiness and renewables. International evidence indicates that ICT development is associated with improved ESG performance, which can strengthen the investment narrative and disclosure environment relevant to green power finance (Zheng et al., 2024, Azizov et al., 2023). Complementary work stresses ICT investment as a strategic imperative for organisational change, consistent with the view that digital infrastructure and institutional learning are necessary conditions for large-scale transition investments (Sahnouni & Kadri, 2025; Jabijev et al., 2022). AI-enabled financial analytics is also entering sustainable markets, with evidence on applying advanced AI to green bond market prediction illustrating how digital tools can support pricing, risk management, and market depth for transition instruments (Sembiyeva et al., 2024). Broader linkages between sustainable-ethical assets and dynamic relationships in financial markets suggest that digital maturity can influence how investors allocate capital across “green” and “ethical” segments, potentially affecting renewable project financing conditions (Nuzula Agustin et al., 2025).

Macroeconomic cycles and structural conditions remain crucial. Evidence from EU countries links the business cycle to renewable energy consumption and sustainable development, indicating that expansion conditions can amplify or dampen renewable uptake (Bușu et al., 2024). In parallel, research on balancing growth and environmental management shows the importance of CO_2 efficiency and renewables within EU development pathways, underscoring that digital governance and AI readiness could matter most where the state can align growth, climate targets, and energy investment planning (Dilanchiev et al., 2024). Because inflation and unemployment dynamics still condition policy space, fiscal support, and household welfare, macro-stability remains a background constraint in which AI-enabled state capacity may improve targeting and efficiency of transition policies (Senci & Afful, 2025; Naumenkova et al., 2025).

Energy-system determinants: capacity deployment, renewable output, and energy security as interacting outcomes

A second major stream maps determinants of renewable electricity penetration and the broader energy-security context. Evidence on renewable penetration in Nordic and Baltic EU countries highlights that renewable development is uneven even in advanced regions, implying that institutional capacity and system management quality can be differentiators beyond resource availability (Štreimikienė, 2024). Systematic review evidence for Greece reinforces that renewable and non-renewable consumption co-evolves with economic structure and policy design, implying that the “capacity-to-output” relationship is mediated by system integration constraints and demand-side conditions (Triantafyllidou et al., 2024). Cross-country causality and cointegration analyses across Nordic and South-Eastern European states further indicate that macroeconomic factors and energy variables are jointly determined over time, strengthening the rationale for governance capabilities that can coordinate interdependent policy levers (Georgescu et al., 2024).

The literature also emphasises that renewables are linked to energy security and resilience, especially under geopolitical risk. Evidence that renewable energy can enhance energy security (under certain dynamics and contexts) implies that accelerating renewables has strategic value, and that AI readiness may shape how effectively countries convert renewable investment into security outcomes (Havrylenko & Myroshnychenko, 2025). Composite approaches to evaluating economic, environmental, and energy security, as well as analyses of sustainable governance in turbulent times, underscore that energy outcomes depend on multidimensional institutional performance, an environment where AI-enabled monitoring and decision support could improve coherence and responsiveness (Mentel et al., 2020; Wołowiec et al., 2022). At the service-delivery level, determinants of consumer satisfaction with energy services highlight that reliability, affordability, and responsiveness are crucial for social acceptance, suggesting a role for data-driven governance in managing distributional trade-offs during renewable energy scaling (Ghimire et al., 2025; Naumenkova et al., 2025).

Operational digitalisation on the demand side also affects the integration of renewable output. Adoption scenarios for home energy management systems illustrate how household-level digital technologies can shape load profiles, flexibility, and the effective utilisation of intermittent renewables (Gualandri & Kuzior, 2023). Because these demand-side tools typically require supportive regulation, standards, and consumer trust, the public-sector readiness component becomes relevant to turning digital adoption into system-level renewable output gains (Murko et al., 2024; Yarovenko et al., 2024).

Innovation ecosystems and entrepreneurship: how readiness shapes the pipeline of renewable projects

Capacity growth is constrained not only by grid and finance, but also by the project pipeline, start-ups, innovators, and investable ventures. Evidence on barriers to clean and digital energy start-ups suggests that access to credit and investor rights protection are key conditions, implying that state capacity and regulatory quality (potentially enhanced by AI-ready governance) influence renewable innovation and project creation (Artyukhov et al., 2024a). This is reinforced by studies of renewable energy entrepreneurship that highlight investment risks and the need for supportive institutional arrangements to mobilise capital and reduce uncertainty (Dobrovolska et al., 2024). Regulatory barriers and bibliometric mapping of entrepreneurship constraints suggest that policy complexity and administrative frictions can hinder renewable deployment, highlighting a concrete pathway where AI-enabled public administration could reduce transaction costs and enhance policy targeting (Myroshnychenko et al., 2024).

A related perspective emphasises decentralisation of energy sources and renewability as a co-evolving research and policy theme, implying that local governance capacity and digital coordination tools are increasingly important for integrating distributed renewable assets into national systems (Belgibayeva et al., 2025). This decentralised landscape also connects to waste and circular economy domains, where AI-enabled industrial automation and municipal waste management can contribute to sustainability performance and potentially to energy-from-waste strategies within broader low-carbon transitions (Kajda & Karwot, 2025; Matvieieva et al., 2023). Technological efficiency in production and consumption within a circular economy framing likewise suggests that country-level technological maturity shapes sustainability outcomes, consistent with the proposition that AI readiness strengthens the efficiency frontier for transition pathways (Gedvilaite & Ginevicius, 2024).

Sectoral digital transformation: supply chains, digital twins, and infrastructure coordination for renewables

Renewable electricity capacity and output depend on equipment supply chains, construction delivery, and operational analytics. Evidence that digital technologies and AI improve supply-chain efficiency supports a mechanism where higher AI readiness can reduce delays, improve procurement transparency, and stabilise renewable build-out (Golubtsov et al., 2025). This aligns with evidence linking AI technology to energy security through global supply-chain channels, suggesting that AI-enabled logistics and risk sensing can influence both the pace of capacity additions and the reliability of renewable output (Wang et al., 2025). The emerging literature on digital twin and industrial metaverse systems also signals a shift towards simulation, predictive maintenance, and complex system modelling, which are directly relevant for grid integration, renewable asset performance, and planning of flexible capacity (Kliestik et al., 2024).

Applied innovation evidence in power generation, such as project-level technological developments, illustrates the ongoing role of engineering innovation in shaping capacity and output trajectories, again implying that public-sector capability (permitting, standards, public procurement) affects diffusion (Ziaja & Lichota, 2024). Studies on AI use in energy and climate security reinforce the expectation that AI readiness can influence strategic planning and risk management around climate-energy objectives, strengthening the readiness-to-renewables link in security-relevant contexts (Mammadov et al., 2025). These mechanisms become especially salient in countries facing heightened geopolitical risks and large infrastructure modernisation needs, including EU–Ukraine integration and reconstruction contexts (Makarenko & Vorontsova, 2024; Vakulenko & Rekunenko, 2025).

The distributional and public health dimension: why output gains must align with welfare outcomes

Renewable electricity expansion is often justified by environmental and health benefits, and this welfare framing shapes political support. Evidence connecting pollution reduction strategies to renewable transition highlights health improvement pathways, implying that capable governments can use data and AI to target interventions and strengthen the credibility of transition policies (Badreddine & Larbi Cherif, 2024). Related work on public health impacts of waste incineration and energy recovery underlines that technology choices require careful governance, monitoring, and communication—areas where AI-ready institutions may better manage externalities and compliance (Matvieieva et al., 2023). Broader AI ethics discussions in public health and automated enforcement remind that technology-led governance must address equity and social justice, suggesting that AI readiness should include safeguards to prevent new forms of exclusion during transition implementation (Haley, 2025; Mura & Stehlíková, 2025).

Distributional concerns are particularly evident in energy poverty. Evidence on government support mechanisms for addressing energy poverty in low-carbon transitions indicates that policy design and administrative capacity matter for protecting vulnerable households while scaling renewables (Naumenkova et al., 2025). This links to consumer behaviour and acceptance dynamics in digital contexts, where AI-driven change can alter trust, habits, and willingness to adopt new services, relevant for demand response, smart metering, and tariff reforms that affect renewable output utilisation (Dias et al., 2023; Gualandri & Kuzior, 2023).

Spatial talent dynamics and institutional spillovers: readiness, brain drain, and capacity to deliver transition

Government AI readiness also has spatial and labour-market implications that can feed back into renewable deployment capacity. Evidence on the relationship between government AI readiness and brain drain in the EU implies that readiness is embedded in broader socio-economic attractiveness and institutional performance; weaker readiness may accelerate talent outflows, undermining the technical and administrative capacity needed for renewable project pipelines (Iuga & Socol, 2024). Organisational leadership and resilience research similarly suggests that AI can enhance sustainable leadership and adaptability, implying that readiness may strengthen institutions' ability to deliver complex transition agendas under uncertainty (Koldovskyi et al., 2025). Governance innovations in e-recruitment and bias-free decision-making further show that AI can improve transparency and administrative quality when used responsibly, an enabling condition for large-scale infrastructure programmes and trust-based regulation (Pollifroni et al., 2025; Yefimenko et al., 2025a).

Broadening the behavioural and societal context: technology acceptance, emotions, and legitimacy

Even when state capacity is strong, renewable outcomes depend on public legitimacy and behavioural responses. Research on consumer eco-emotions in novel sustainability markets signals that emotional and value-based responses can influence acceptance of environmentally framed innovations, suggesting that governments need communication and engagement capacity alongside technical readiness (Kouarfaté et al., 2024). Evidence on AI-driven customer feedback management and content analysis highlights how AI can support responsive governance and service improvement by processing large-scale citizen input—potentially relevant for siting decisions, community acceptance, and continuous improvement in renewable programmes (Kildei et al., 2025; Murko et al., 2024). Studies on the creative economy and expert perceptions of AI adoption underscore that opportunities and barriers are context-specific, reinforcing the argument that readiness includes institutional learning and adaptation rather than simply technology acquisition (Schinello, 2025; Yarovenko et al., 2024).

Technology acceptance evidence from adjacent domains, such as digital insurance adoption among older adults and smart financial strategies for ageing populations, illustrates that demographic factors, trust, and perceived value shape uptake of digital services, implying parallels for smart energy services and the household-facing components of renewable integration (Batizani, 2024; Chandran & Ittimani Tholath, 2025). In parallel, occupational safety applications of AI-based image analysis highlight that AI readiness can improve compliance and risk management in construction-like environments, offering an additional pathway for safer, more efficient renewable infrastructure delivery (Zaryczańska & Karwot, 2025).

Ukraine–EU transition context: reconstruction, integration, and the strategic role of readiness

In transition and reconstruction settings, the linkage between AI readiness and renewable electricity outcomes becomes particularly policy-relevant. Evidence on green energy in Ukraine highlights the state of development, public demand, and trends, implying that readiness and governance quality may shape how quickly renewable capacity can scale and how effectively output is integrated into a resilient system (Kuzior et al., 2021). EU–Ukraine benchmarking work and clean energy cooperation initiatives reinforce that harmonisation, institutional capacity, and project governance are central to transition success, suggesting that government AI readiness can support the administrative and analytical demands of integration and rebuilding (Makarenko & Vorontsova, 2024; Vakulenko & Rekunenko, 2025). Environmental tax reform and carbon tax research mapping further position fiscal instruments as complements to capability-driven implementation, implying that AI-ready institutions may better design, monitor, and enforce market-based transition policies while limiting unintended effects (Kusumawati et al., 2025; Samusevych et al., 2024).

Evidence linking the share of renewables to CO_2 emissions over long horizons supports the basic motivation for capacity and output expansion, but it also implies the need for consistent governance to maintain policy credibility and investment continuity across cycles (Tutar & Bilan, 2025; Dilanchiev et al., 2024). Finally, sectoral evidence on climate mitigation performance in tourism destinations indicates that transition performance varies across sectors and regions, again pointing to the value of state capability and digital governance tools to coordinate cross-sector decarbonisation efforts (Streimikiene & Kyriakopoulos, 2024).

Overall, the existing literature implies that government AI readiness can shape renewable electricity capacity and output through multiple, mutually reinforcing pathways: (i) higher-quality public governance and ethical safeguards that enable trustworthy digital decision-making; (ii) stronger human capital and organisational adoption capacity; (iii) better mobilisation of sustainable finance and improved ESG environments; (iv) more efficient supply chains and project delivery; and (v) improved distributional targeting and legitimacy that stabilise transition policy over time (Androniceanu, 2024; Zheng et al., 2024; Golubtsov et al., 2025; Naumenkova et al., 2025; Wołowiec et al., 2022). However, the same landscape suggests that these effects are conditional on complementary institutions and social acceptance, meaning readiness is unlikely to translate into renewable outcomes uniformly across countries and phases of transition (Mujtaba, 2025; Höller et al., 2023; Iuga & Socol, 2024). This motivates empirical analysis that explicitly connects government AI readiness to renewable electricity capacity and output while accounting for institutional quality, macroeconomic conditions, and energy-system constraints, especially in turbulent geopolitical environments where the payoff to state capability may be highest (Havrylenko & Myroshnychenko, 2025; Mammadov et al., 2025; Mentel et al., 2020).

This research aims to empirically examine the extent to which Government AI Readiness influences the development of renewable energy systems by assessing its relationship with (i) Total Renewable Electricity Installed Capacity and (ii) Total Renewable Electricity Generation across a global panel of countries.

This study formulates two core hypotheses based on the theoretical link between technological readiness, institutional capacity, and the transition to sustainable energy systems. The first hypothesis (H1) posits that higher Government AI Readiness is positively associated with greater Total Renewable Electricity Installed Capacity. This assumption reflects that AI readiness enhances a country's ability to plan, finance, and deploy renewable energy projects by improving decision-making, optimising resource allocation, and streamlining project implementation. The second hypothesis (H2) proposes that higher Government AI Readiness is positively associated with greater Total Renewable Electricity Generation. This relationship is expected because AI-driven tools can optimise system operations, improve grid integration of intermittent renewables, and enhance efficiency in energy production. These hypotheses aim to capture both the infrastructural and operational dimensions of the renewable energy sector that could be influenced by a country's preparedness to adopt and utilise artificial intelligence technologies.

METHODS

Data and variables

The analysis employs an unbalanced panel dataset covering 179–183 countries (the samples of countries for analysis are presented in Appendix A) over the period 2020–2024. The primary independent variable is the Government AI Readiness Index (*x1*), compiled annually by the Oxford Insights AI Readiness Index database (Oxford Insights, n.d.). This index measures a nation's preparedness to implement and leverage artificial intelligence across governance, infrastructure, and human capital dimensions.

Two dependent variables are examined:

1. Total Renewable Electricity Installed Capacity (*y1*, MW), and
2. Total Renewable Electricity Generation (*y2*, GWh),

sourced from the International Renewable Energy Agency Statistics Database (IRENA, n.d.).

The primary control variable is GDP per capita (constant 2015 US$) (*x3*), obtained from the World Bank's World Development Indicators (World Bank, n.d.), serving as a proxy for economic development and financial capacity to invest in renewable energy.

Data transformation and normalisation

Descriptive statistics revealed that *y1*, *y2*, and *x3* exhibited substantial positive skewness and leptokurtosis, indicating non-normal distributions and the presence of extreme values. The Box–Cox procedure was applied to each variable using intercept-only models to determine the optimal transformation. These transformations reduce skewness, mitigate the influence of outliers, stabilise variance, and align with standard econometric practice in energy economics, where proportional changes are often of primary interest.

Econometric specification

The empirical analysis estimates Fixed Effects (FE) and Random Effects (RE) panel regression models using the plm package in R. The general model specification is:

$$y_{it}=\beta_0+\beta_1 x1_{it}+\beta_2 x3_{it}+\mu_i+\epsilon_{it}$$

Where y_{it} represents either $ln(y1)$ or $ln(y2)$ for country *i* in year *t*, $x1_{it}$ is the Government AI Readiness Index, $x3_{it}$ is *ln(GDP per capita)*, μ_i denotes unobserved country-specific effects, and ϵ_{it} is the idiosyncratic error term.

The FE model controls for time-invariant unobserved heterogeneity, while the RE model assumes these effects are uncorrelated with the regressors. Model selection between FE and RE was guided by the Hausman test, where a statistically significant result favours the FE specification.

Diagnostic testing

Diagnostic tests were performed on the FE models to check for heteroskedasticity and serial correlation, ensuring robust inference.

- Heteroskedasticity was tested using the studentised Breusch–Pagan test.
- Serial correlation was examined using both the Breusch–Godfrey/Wooldridge test for panel models and Wooldridge's test for autocorrelation in FE panels.

For both *y1_log* and *y2_log* models, the null hypotheses of homoskedasticity and no serial correlation were rejected, indicating violations of classical OLS assumptions.

Robust standard errors

Given heteroskedasticity and autocorrelation, all FE models were re-estimated using cluster-robust standard errors to produce consistent estimates. Two clustering strategies were applied:

1. One-way clustering by entity (country), and
2. Two-way clustering by both entity and year.

In all cases, results were robust to the choice of clustering dimension, and statistical significance levels remained consistent across specifications.

All statistical calculations, data transformations, model estimations, and diagnostic tests were conducted in RStudio (version 4.4.0), ensuring the reproducibility and transparency of the analytical process.

RESULTS

AI readiness and total renewable electricity installed capacity

Table B1, Appendix B, presents the descriptive statistics for the panel dataset, which comprises 901 country–year observations from 2020 to 2024. The dataset covers 183 countries, with the panel balanced in terms of temporal coverage.

The Government AI Readiness Index (x1) has a mean score of 46.08 (SD = 16.71), ranging from 13.46 to 88.16. The moderate skewness (0.46) and slight platykurtosis (–0.89) indicate a distribution that is close to symmetric, with no severe deviations from normality.

The dependent variable Total Renewable Electricity Installed Capacity (MW) (y1) exhibits substantial dispersion (mean = 19,292.18; SD = 103,500.04) and an extensive range (0.43 to 1,817,956.01). The extreme positive skewness (12.18) and very high kurtosis (171.46) indicate a highly non-normal distribution with strong right-tail outliers.

Similarly, GDP per capita (constant 2015 US$) (x3) is positively skewed (2.21) and leptokurtic (5.16), indicating a heavy-tailed distribution and substantial cross-country variation.

In contrast, Total Renewable Electricity Generation (GWh) (y2, not displayed in this excerpt) exhibits comparable distributional patterns to y1, with high variability and right skewness, reflecting the concentration of renewable energy generation in a subset of high-capacity countries.

Given the extreme skewness and kurtosis in y1and x3, statistical transformations – such as logarithmic or Box–Cox – are necessary to normalise distributions, reduce the impact of extreme values, and satisfy econometric model assumptions.

A Box–Cox transformation was applied using an intercept-only model for each variable to identify the most appropriate functional form for the highly skewed variables. For Total Renewable Electricity Installed Capacity (MW) (y1), the estimated Box–Cox parameter λ was 0.0606, which lies very close to zero. This outcome indicates that a natural logarithm transformation is optimal, as it effectively reduces the extreme right skewness (12.18) and high kurtosis (171.46) observed in the descriptive statistics. The log transformation mitigates the disproportionate influence of a small number of high-capacity countries, resulting in a more symmetrical distribution suitable for regression analysis.

For GDP per capita (constant 2015 US$) (x3), the estimated λ was –0.0202, again essentially equivalent to zero in Box–Cox terms. This confirms that a natural logarithm transformation is the most appropriate choice. Applying the log form reduces the moderate right skewness (2.21) and elevated kurtosis (5.16), stabilises the variance, and aligns with standard econometric practice for income variables, where proportional differences are analytically more relevant than absolute differences.

Accordingly, y1 and x3 were transformed using the natural logarithm before further econometric modelling. This ensures that distributional assumptions are better satisfied and that extreme values do not unduly influence estimated relationships.

To account for the severe skewness and kurtosis identified in the descriptive analysis, Total Renewable Electricity Installed Capacity (MW) (y1) and GDP per capita (x3) were transformed using the natural logarithm prior to modelling. The FE model (Table 2) reveals that both the Government AI Readiness Index (x1) and log GDP per capita (x3_log) are positive and highly statistically significant predictors of y1_log. Specifically, a one-unit increase in x1 is associated with a 1.71% increase in installed renewable capacity, holding other factors constant. In comparison, a 1% increase in GDP per capita corresponds to an almost proportional 0.95% increase in capacity. The within R^2 is 0.091, indicating modest explanatory power for within-country variation.

The RE model (Table 1) also reports statistically significant coefficients for both x1 and x3_log, with slightly different magnitudes: a one-unit increase in x1 is linked to a 2.87% increase in installed capacity, and a 1% rise in GDP per capita corresponds to a 0.53% increase. The overall R^2 (0.088) is similar to the FE specification.

The Hausman test ($\chi^2(2) = 72.877$, $p < 0.001$) strongly rejects the null hypothesis that the RE estimator is consistent, indicating that the FE model should be preferred for inference.

Table 1. The outputs of FE and RE models for y1_log (Total Renewable Electricity Installed Capacity, log-transformed) [Source: authors' calculations in R Studio]

Variable/ model stat	One-way (individual) Fixed Effect Within Model	One-way (individual) effect Random Effect Model (Swamy-Arora's transformation)
N (obs)	867	
Entities	183	
Time	2–5 years	
(Intercept)	–	0.9395 (0.2810)
x1 (Government AI Readiness Index)	0.0171 (0.0000)***	0.0287 (0.0000)***
x3 (GDP per capita, constant 2015 US$)	0.9546 (0.0000)***	0.5270 (0.0000)***
Model stats		
Within R^2	0.0908	–
Overall R^2	–	0.0878
Adj. R^2	–0.1545	0.0857
F-statistic	34.064 (0.0001)***	–
Chi²	–	124.822 (<0.0001)***
Hausman test result		
$\chi^2(2)$		72.877
p		<0.001

Note: '–' – not calculated for this type of model.
Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Diagnostic tests were conducted to assess the validity of the error structure in the Fixed Effects specification for y1_log. The Breusch–Pagan test (BP = 37.16, df = 2, $p < 0.001$) strongly rejects the null hypothesis of homoskedasticity, indicating the presence of heteroskedasticity in the residuals.

Tests for autocorrelation also provided consistent evidence of serial correlation in the idiosyncratic errors. The Breusch–Godfrey/Wooldridge test for serial correlation in panel models yielded a $\chi^2(2)$ statistic of 145.87 ($p < 0.001$), while Wooldridge's test for autocorrelation in FE panels reported an F-statistic of 71.90 ($p < 0.001$). Both results reject the null of no serial correlation.

The joint presence of heteroskedasticity and serial correlation violates the classical OLS assumptions, leading to biased standard errors. Therefore, subsequent inference for the Fixed Effects model was based on cluster-robust standard errors to ensure consistency and reliability of statistical inference.

Following the detection of heteroskedasticity (Breusch–Pagan test, $p < 0.001$) and serial correlation (Breusch–Godfrey/Wooldridge and Wooldridge FE tests, both $p < 0.001$) in the residuals of the Fixed Effects model, the standard error estimates were adjusted using cluster-robust methods. This adjustment ensures that statistical inference remains valid despite violations of the classical OLS assumptions, which, if ignored, can lead to underestimation of standard errors and inflation of t-statistics.

The re-estimation of the Fixed Effects model with one-way clustering by entity (Table 2) confirms the robustness of the results. The Government AI Readiness Index (x1) and log GDP per capita (x3_log) retain positive and statistically significant coefficients at the 1%. Substantively, a one-unit increase in x1 is associated with an estimated 1.71% increase in total renewable electricity installed capacity. In comparison, a 1% increase in GDP per capita corresponds to an almost proportional 0.95% increase, holding other factors constant.

Table 2. Fixed Effects model with cluster-robust SE (one-way, clustered by entity) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0171	0.00568	3.017	0.0026 **
x3_log (GDP per capita, log)	0.9546	0.30631	3.116	0.0019 **
Model stats				
N (obs)	867			
Entities	183			
Time	2–5 years			
Within R²	0.0908			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Applying two-way clustering by entity and time (Table 3) yields identical coefficient estimates and robust standard errors to the one-way clustered results. This indicates that the significance and magnitude of the estimated effects are not sensitive to the clustering dimension, further strengthening confidence in the findings.

The consistent statistical significance of x1 and x3_log across both clustering approaches suggests a stable and economically meaningful relationship between government AI readiness, economic development, and the deployment of renewable electricity capacity in the sampled countries.

Table 3. Fixed Effects model with cluster-robust SE (two-way, clustered by entity and time) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0171	0.00568	3.017	0.0026 **
x3_log (GDP per capita, log)	0.9546	0.30631	3.116	0.0019 **
Model stats				
N (obs)	867			
Entities	183			
Time	2–5 years			
Within R^2	0.0908			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

AI readiness and total renewable electricity generation

Table B2 (Appendix B) presents the descriptive statistics for the panel dataset, which comprises 687 country–year observations from 2020 to 2023, covering 179 countries. The Government AI Readiness Index (x1) shows a mean score of 45.62 (SD = 16.63) and a range from 13.46 to 88.16, with moderate positive skewness (0.49) and mild platykurtosis (–0.86), indicating an approximately symmetric distribution without extreme tails.

In contrast, Total Renewable Electricity Generation (GWh) (y2) exhibits very high dispersion (mean = 47,093.31; SD = 212,454.99) and an extensive range from 0.14 to 2,842,825.71. The extreme right skewness (9.84) and high kurtosis (110.06) reveal a highly non-normal distribution with substantial outliers concentrated in a small subset of high-generation countries.

GDP per capita (constant 2015 US$) (x3) also displays considerable variability (mean = 14,304.92; SD = 19,575.53) with values ranging from 253.45 to 110,873.19. The positive skewness (2.18) and leptokurtosis (5.00) indicate a heavy right tail, with a few high-income countries significantly above the median.

These results suggest that both y2 and x3 deviate significantly from normality, warranting logarithmic or Box–Cox transformations prior to econometric modelling to reduce skewness, mitigate the influence of extreme values, and improve compliance with model assumptions.

To address the severe skewness and kurtosis observed in the descriptive statistics, the Box–Cox transformation was applied to Total Renewable Electricity Generation (y2) and GDP per capita (x3) using an intercept-only model. For y2, the estimated Box–Cox parameter was λ = 0.0606, effectively zero in practical terms, indicating that a natural logarithm transformation is optimal. This transformation substantially reduces the extreme right skewness (9.84) and high kurtosis (110.06), mitigating the disproportionate influence of many high-generation countries.

For x3, the estimated λ was –0.0202, which is effectively zero, supporting the use of a natural logarithm transformation. This adjustment corrects for the variable's positive skewness (2.18) and leptokurtosis (5.00), which arise from a few high-income economies far exceeding the sample median.

Accordingly, both variables were log-transformed before econometric modelling to improve distributional properties, stabilise variance, and ensure that coefficient estimates reflect proportional rather than absolute changes.

To analyse the relationship between Total Renewable Electricity Generation (y2_log), the Government AI Readiness Index (x1), and log GDP per capita (x3_log), both Fixed Effects (FE) and Random Effects (RE) panel models were estimated.

The FE model (Table 4), estimated on an unbalanced panel of 179 countries over 2–4 years ($N = 687$), indicates that x3_log is positively and highly statistically significant ($\beta = 0.960$, $p < 0.001$), suggesting that a 1% increase in GDP per capita is associated with an almost proportional 0.96% increase in renewable electricity generation within countries over time. The coefficient for x1 is positive ($\beta = 0.0081$) but only marginally significant at the 10% level ($p = 0.086$), indicating a weaker within-country association between government AI readiness and renewable generation capacity. The within R^2 of 0.063 indicates modest explanatory power for within-country variation.

In the RE model (Table 4), both x1 ($\beta = 0.0200$, $p < 0.001$) and x3_log ($\beta = 0.5585$, $p < 0.001$) are positive and highly statistically significant. Here, the x1 effect is larger compared to the FE estimate, while the x3_log effect is more negligible, reflecting the inclusion of both within- and between-country variation in the RE estimation.

The Hausman test ($\chi^2(2) = 53.3$, $p < 0.0001$) rejects the null hypothesis of no systematic difference between FE and RE estimators, indicating that the RE model is inconsistent and that the FE model should be preferred for inference.

Table 4. FE and RE models for y2_log (Total Renewable Electricity Generation, log-transformed) [Source: authors' calculations in R Studio]

Variable	One-way (individual) effect Within Model	One-way (individual) effect Random Effect Model (Swamy-Arora's transformation)
N (obs)	687	
Entities	179	
Time	2–4 years	
(Intercept)	–	1.9815 (0.0456) *
x1 (Government AI Readiness Index)	0.0081 (0.0859) .	0.0200 (0.0001) ***
x3_log (GDP per capita, log)	0.9605 (0.0000) ***	0.5585 (0.0000) ***
Model stats		
Within R²	0.0627	–
Overall R²	–	0.0440
Adj. R²	–0.2707	0.0412
F-statistic	16.934 (p < 0.0001)	–
Chi²	–	65.747 (p < 0.0001)
Hausman test result		
χ²(2)		53.3
p		<0.0001

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Diagnostic tests were applied to the Fixed Effects model for y2_log to evaluate the validity of the error structure. The studentised Breusch–Pagan test ($BP = 32.78$, $df = 2$, $p < 0.001$) rejects the null hypothesis of homoskedasticity, indicating the presence of heteroskedasticity in the residuals.

Tests for autocorrelation also point to significant serial correlation. The Breusch–Godfrey/Wooldridge test for serial correlation in panel models reports a $\chi^2(2) = 79.20$ ($p < 0.001$), and Wooldridge's test for serial correlation in FE panels yields an F-statistic of 12.70 ($p < 0.001$). Both results confirm the rejection of the null hypothesis of no serial correlation.

The joint presence of heteroskedasticity and serial correlation violates the classical OLS assumptions for the error term, potentially biasing standard errors and leading to unreliable inference. To address this, subsequent model estimation for y2_log is conducted using cluster-robust standard errors, ensuring consistent and valid statistical inference.

Given the detection of heteroskedasticity and serial correlation in the error structure of the Fixed Effects model for y2_log, the model was re-estimated with cluster-robust standard errors, clustering by entity (country). As shown in Table 5, the Government AI Readiness Index (x1) coefficient remains positive ($\beta = 0.0081$). However, it is no longer statistically significant ($p = 0.155$), indicating that there is insufficient evidence to conclude a within-country effect of AI readiness on renewable electricity generation once robust inference is applied. In contrast, log GDP per capita (x3_log) retains a positive and highly significant relationship with y2_log ($\beta = 0.9605$, $p < 0.001$), suggesting that a 1% increase in GDP per capita is associated with an almost proportional 0.96% increase in renewable electricity generation.

Table 5. FE model with cluster-robust SE (one-way, clustered by entity) for y2_log [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0081	0.00571	1.424	0.1552
x3_log (GDP per capita, log)	0.9605	0.24083	3.988	0.0001 ***
Model stats				
N (obs)	687			
Entities	179			
Time	2–4 years			
Within R²	0.0627			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

Table 6. FE model with cluster-robust SE (two-way, clustered by entity and time) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0081	0.00571	1.424	0.1552
x3_log (GDP per capita, log)	0.9605	0.24083	3.988	0.0001 ***
Model stats				
N (obs)	687			
Entities	179			
Time	2–4 years			
Within R²	0.0627			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

Applying two-way clustering by both entity and time produced identical coefficient estimates and robust standard errors, confirming the stability of the results across clustering specifications. This robustness suggests that the observed GDP per capita effect is consistent and not sensitive to alternative error correlation structures. In contrast, the effect of AI readiness remains weak when accounting for potential violations of classical OLS assumptions.

The observed difference in the influence of the Government AI Readiness Index between the two dependent variables suggests that AI readiness may primarily facilitate the planning, deployment, and installation of renewable energy capacity rather than directly translating into higher electricity generation within the short time frame of the panel. High AI readiness often reflects greater digital infrastructure, advanced data management capabilities, and institutional capacity to integrate emerging technologies into energy planning. These capabilities can streamline permitting processes, optimise site selection through AI-assisted geospatial analysis, and improve investment targeting – all factors that accelerate the installation of renewable assets.

However, translating installed capacity into actual electricity generation depends on additional factors not necessarily captured by AI readiness. These include variability in renewable resource availability (e.g., wind speeds, solar irradiation), operational efficiency, grid integration, storage capacity, and maintenance regimes. Countries with high AI readiness may therefore be able to expand capacity rapidly. However, suppose grid constraints, intermittent resource availability, or operational inefficiencies persist. In that case, this capacity may not be fully utilised, resulting in no statistically significant effect on total generation during the observed period. This distinction underscores the importance of complementary investments in grid infrastructure, storage solutions, and operational optimisation to ensure that capacity gains lead to proportional increases in renewable electricity output.

DISCUSSION

The empirical results indicate a statistically significant positive relationship between the Government AI Readiness Index and the total installed capacity of renewable electricity. In contrast, no significant effect was observed for total renewable electricity generation. This finding suggests that AI readiness at the governmental level may play a stronger role in enabling the development of renewable energy infrastructure than in directly influencing the operational output of these assets. The result aligns with studies highlighting AI's potential to improve planning, investment allocation, and capacity-building in the energy sector through enhanced forecasting, project management, and optimisation of infrastructure deployment (Ibadildin et al., 2025; Koldovskyi et al., 2025; Wang et al., 2025). These capabilities may expedite the installation of capacity. However, the absence of a significant effect on generation indicates that additional operational, technical, or market factors, such as intermittency, grid constraints, or policy incentives, continue to determine actual output levels (Triantafyllidou et al., 2024; Havrylenko & Myroshnychenko, 2025).

The stronger link with installed capacity can be further explained by AI readiness supporting strategic-level decisions and long-term infrastructure investment, as observed in public governance and clean energy transition research (Murko et al., 2024; Naumenkova et al., 2025). AI-enabled analytics help governments identify optimal sites for renewable installations, improve permitting processes, and coordinate financing mechanisms (Dobrovolska et al., 2024; Myroshnychenko et al., 2024). However, these benefits may not automatically translate into higher generation without parallel advances in grid integration, storage solutions, and demand-side management (Gualandri & Kuzior, 2023; Golubtsov et al., 2025).

The non-significant relationship with generation echoes the conclusions of previous studies, which emphasise the importance of operational AI applications (such as real-time energy dispatch, predictive maintenance, and supply-demand balancing) for achieving consistent output growth (Wang et al., 2025; Kildei et al., 2025). The absence of such operational integration at scale in many countries could explain why government-level AI readiness has yet to yield a measurable effect on generation. This finding is consistent with those from renewable energy resilience studies, which emphasise the need for targeted technological investments and adaptive policy frameworks to address challenges related to variability and intermittency (Ghimire et al., 2025; Vakulenko & Rekunenko, 2025).

Overall, the results suggest that while AI readiness can catalyse infrastructure expansion, its impact on energy output requires a more direct integration of AI into grid operations, market mechanisms, and renewable plant management. Future energy strategies should therefore combine AI-driven planning with targeted operational AI applications to bridge the gap between installed capacity and actual generation. Such integrated approaches are likely to yield higher returns in terms of capacity utilisation and system efficiency (Yefimenko et al., 2025a; Artyukhov et al., 2024b).

Limitations. While the study provides robust evidence on the relationship between government AI readiness, economic development, and renewable energy deployment, several limitations should be acknowledged. First, the panel dataset covers a relatively short period (2020–2024), which restricts the ability to capture long-term dynamics and potential lagged effects of AI readiness on renewable energy outcomes. Second, while comprehensive, the Government AI Readiness Index may not fully reflect the actual AI implementation capacity or the effectiveness of AI-related policies in the energy sector, potentially leading to measurement bias. Third, although transformations and robust estimation techniques were applied to address skewness, heteroskedasticity, and serial correlation, unobserved time-varying factors, such as changes in national energy policies, geopolitical events, or technological breakthroughs, may still confound the estimated relationships. Fourth, the analysis is limited to macro-level country data; sectoral, regional, or plant-level variations in renewable energy deployment and generation could not be explored due to data unavailability. Finally, the study assumes data comparability across countries, but differences in statistical reporting practices, particularly for renewable electricity generation and capacity, may introduce cross-country measurement inconsistencies.

Future research could extend the temporal scope to include a longer time horizon, allowing for the assessment of long-term and lagged effects of AI readiness on renewable energy transitions. Incorporating sector-specific or regional-level data could provide deeper insights into how AI influences renewable energy outcomes. Additionally, future studies may benefit from integrating qualitative assessments of AI policy implementation, exploring the interaction between AI readiness and other enabling factors such as grid modernisation, energy storage, and market regulation. Comparative case studies between high- and low-AI-readiness countries could also shed light on best practices and contextual constraints in leveraging AI for renewable energy development.

CONCLUSIONS

The primary aim of this research was to investigate the extent to which Government AI Readiness influences renewable energy development, focusing on two key outcomes: Total Renewable Electricity Installed Capacity and Total Renewable Electricity Generation. By formulating and testing two hypotheses, the study sought to determine whether countries with higher AI readiness can expand renewable energy infrastructure and increase renewable electricity output.

The analysis was based on an unbalanced global panel dataset covering 183 countries from 2020 to 2024. The Government AI Readiness Index, the core explanatory variable, was obtained from the Oxford Insights database. At the same time, renewable energy indicators were sourced from IRENA, and GDP per capita from the World Bank. Severe skewness and kurtosis in *y1*, *y2*, and *x3* were addressed through natural logarithm transformations, supported by Box–Cox analysis. Econometric modelling employed both Fixed Effects and Random Effects specifications, with the Hausman test guiding model selection. Diagnostic tests identified heteroskedasticity and serial correlation, and all FE estimates were reported with cluster-robust standard errors to ensure valid inference.

The results reveal that both Government AI Readiness and GDP per capita are positive and statistically significant predictors of installed capacity. Specifically, a one-unit increase in AI readiness is associated with a 1.71% increase in installed renewable capacity, while a 1% increase in GDP per capita corresponds to a 0.95% increase in capacity. For electricity generation, GDP per capita remains a strong and significant predictor (0.96% increase in generation per 1% GDP per capita growth). In contrast, the effect of AI readiness is positive but statistically insignificant once robust errors are applied. This suggests that while AI readiness supports the deployment of renewable infrastructure, its impact on actual generation may depend on additional operational, technical, and resource factors.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

From a policy perspective, the findings highlight the potential of AI readiness as a facilitator of renewable energy capacity expansion. Governments aiming to accelerate the deployment of renewable energy sources should consider integrating AI-driven tools into project planning, resource mapping, permitting, and investment allocation processes. However, complementary investments are needed in grid modernisation, energy storage, and operational optimisation to translate installed capacity into tangible generation gains. Furthermore, enhancing AI readiness should go hand in hand with targeted policies that improve the efficiency, reliability, and utilisation rates of renewable energy assets. Such an integrated approach can maximise the benefits of both technological preparedness and clean energy transitions, ultimately contributing to global decarbonisation goals.

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Appendix A

The sample of countries in the analysis of the interaction of the AI readiness and total renewable electricity installed capacity

Afghanistan,
Albania,
Algeria,
Andorra,
Angola,
Antigua and Barbuda,
Argentina,
Armenia,
Australia,
Austria,
Azerbaijan,
Bahamas,
Bahrain,
Bangladesh,
Barbados,
Belarus,
Belgium,
Belize,
Benin,
Bhutan,
Bolivia (Plurinational State of),
Bosnia and Herzegovina,
Botswana,
Brazil,
Brunei Darussalam,
Bulgaria,
Burkina Faso,
Burundi,
Cabo Verde,
Cambodia,
Cameroon,
Canada,
Central African Republic,
Chad,
Chile,
China,
Colombia,
Comoros,
Congo,
Costa Rica,
Côte d'Ivoire,
Croatia,
Cuba,
Cyprus,
Czechia,
Democratic Republic of the Congo,
Denmark,
Djibouti,
Dominica,
Dominican Republic,
Ecuador,
Egypt,
El Salvador,
Equatorial Guinea,
Estonia,
Eswatini,
Ethiopia,
Fiji,
Finland,
France,
Gabon,
Gambia (Republic of the),
Georgia,
Germany,
Ghana,
Greece,
Grenada,
Guatemala,
Guinea,
Guinea-Bissau,
Guyana,
Haiti,
Honduras,
Hungary,
Iceland,
India,
Indonesia,
Iran (Islamic Republic of),
Iraq,
Ireland,
Israel,
Italy,
Jamaica,
Japan,
Jordan,
Kazakhstan,
Kenya,
Kiribati,
Kuwait,
Kyrgyzstan,
Lao People's Democratic Republic,
Latvia,
Lebanon,
Lesotho,
Liberia,
Libya,
Lithuania,
Luxembourg,
Madagascar,
Malawi,
Malaysia,
Maldives,
Mali,
Malta,
Marshall Islands,
Mauritania,
Mauritius,
Mexico,
Mongolia,
Montenegro,
Morocco,
Mozambique,
Myanmar,
Namibia,
Nepal,
Netherlands,
New Zealand,
Nicaragua,
Niger,
Nigeria,
North Macedonia,
Norway,
Oman,
Pakistan,
Panama,
Papua New Guinea,
Paraguay,
Peru,
Philippines,
Poland,
Portugal,
Qatar,
Republic of Moldova,
Republic of Korea,
Romania,
Russian Federation,
Rwanda,
Saint Kitts and Nevis,
Saint Lucia,
Saint Vincent and the Grenadines,
Samoa,
São Tomé and Príncipe,
Saudi Arabia,
Senegal,
Serbia,
Seychelles,

Sierra Leone,
Singapore,
Slovakia,
Slovenia,
Solomon Islands,
Somalia,
South Africa,
Spain,
Sri Lanka,
Sudan,
Suriname,
Sweden,
Switzerland,
Syrian Arab Republic,
Taiwan,
Tajikistan,
Thailand,
Timor-Leste,
Togo,
Tonga,
Trinidad and Tobago,
Tunisia,
Türkiye,
Turkmenistan,
Uganda,
Ukraine,
United Arab Emirates,
United Kingdom,
United Republic of Tanzania,
United States of America,
Uruguay,
Uzbekistan,
Vanuatu,
Viet Nam,
Yemen,
Zambia,
Zimbabwe.

The sample of countries in the analysis of the interaction of the AI readiness and total renewable electricity generation

Afghanistan
Albania
Algeria
Andorra
Angola
Antigua and Barbuda
Argentina
Armenia
Australia
Austria
Azerbaijan
Bahamas
Bahrain
Bangladesh
Barbados
Belarus
Belgium
Belize
Benin
Bhutan
Bolivia(Plurinational State of)
Bosnia and Herzegovina
Botswana
Brazil
Brunei Darussalam
Bulgaria
Burkina Faso
Burundi
Cabo Verde
Cambodia
Cameroon
Canada
Central African Republic
Chad
Chile
China
Colombia
Comoros
Congo
Costa Rica
Côte d'Ivoire
Croatia
Cuba
Cyprus
Czechia
Democratic Republic of the Congo
Denmark
Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Estonia
Eswatini
Ethiopia
Fiji
Finland
France
Gabon
Gambia(Republic of the)
Georgia
Germany
Ghana
Greece
Grenada
Guatemala
Guinea
Guinea-Bissau
Guyana
Haiti
Honduras
Hungary
Iceland
India
Indonesia
Iran(Islamic Republic of)
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Kiribati
Kuwait
Kyrgyzstan
Lao People's Democratic Republic
Latvia
Lebanon
Lesotho
Liberia
Libya
Lithuania
Luxembourg
Madagascar
Malawi
Malaysia
Maldives
Mali
Malta
Mauritania
Mauritius
Mexico
Mongolia
Montenegro
Morocco
Mozambique
Myanmar

Namibia
Nepal
Netherlands
New Zealand
Nicaragua
Niger
Nigeria
North Macedonia
Norway
Oman
Pakistan
Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland
Portugal
Qatar
Republic of Korea
Republic of Moldova
Romania
Russian Federation
Rwanda
Saint Lucia
Saint Vincent and the Grenadines
Samoa
São Tomé and Príncipe
Saudi Arabia
Senegal
Serbia
Seychelles
SierraLeone
Singapore
Slovakia
Slovenia
Solomon Islands
South Africa
Spain
Sri Lanka
Sudan
Suriname
Sweden
Switzerland
Syrian Arab Republic
Taiwan
Tajikistan
Thailand
Timor-Leste
Togo
Tonga
Trinidad and Tobago
Tunisia
Türkiye
Turkmenistan
Uganda
Ukraine
United Arab Emirates
United Kingdom
United Republic of Tanzania
United States of America
Uruguay
Uzbekistan
Vanuatu
Viet Nam
Yemen
Zambia
Zimbabwe

Appendix B

Table B1. Descriptive statistics of key variables in the panel dataset for y1 analysis [Source: authors' calculations in R Studio]

Variable	Government AI Readiness Index (x1)	Total Renewable Electricity Installed Capacity (MW) (y1)	GDP per capita (constant 2015 US$) (x3)
N	867	867	867
Mean	46,08	19,292,18	14,134,40
SD	16,71	103,500,04	19,302,90
Median	41,83	1,660,14	5,828,07
Trimmed	45,15	3,915,39	9,899,10
MAD	17,17	2,408,31	6,974,67
Min	13,46	0,43	253,45
Max	88,16	1,817,956,01	110,873,19
Range	74,7	1,817,955,60	110,619,70
Skew	0,46	12,18	2,21
Kurtosis	–0,89	171,46	5,16
SE	0,57	3,448,09	643,43

Table B2. Descriptive statistics of key variables in the panel dataset for the y2 analysis [Source: authors' calculations in R Studio]

Variable	x1 (Government AI Readiness Index)	y2 (Total Renewable Electricity Generation, GWh)	x3 (GDP per capita, constant 2015 US$)
N	687	687	687
Mean	45,62	47,093,31	14,304,92
SD	16,63	212,454,99	19,575,53
Median	41,5	5,268,99	5,831,83
Trimmed	44,61	11,465,93	10,050,95
MAD	16,89	7,692,47	6,995,32
Min	13,46	0,14	253,45
Max	88,16	2,842,825,71	110,873,19
Range	74,7	2,842,825,57	110,619,74
Skew	0,49	9,84	2,18
Kurtosis	–0,86	110,06	5
SE	0,63	8,105,66	746,85