










“Bridging digital innovation and energy justice: The role of artificial intelligence in advancing energy equity”

AUTHORS

Oxana Kirichok 
Yuliia Orlovska
Gulnara Zhanseitova 

Alvina Oriekhova 

Denys Babaiev 
Oleksii Havrylenko 
Tetiana Vasylieva 


ARTICLE INFO

Oxana Kirichok, Yuliia Orlovska, Gulnara Zhanseitova, Alvina Oriekhova, Denys Babaiev, Oleksii Havrylenko and Tetiana Vasylieva (2025). Bridging digital innovation and energy justice: The role of artificial intelligence in advancing energy equity. *Environmental Economics*, 16(4), 166-181.
doi:[10.21511/ee.16\(4\).2025.11](https://doi.org/10.21511/ee.16(4).2025.11)

DOI

[http://dx.doi.org/10.21511/ee.16\(4\).2025.11](http://dx.doi.org/10.21511/ee.16(4).2025.11)

RELEASED ON

Wednesday, 17 December 2025

RECEIVED ON

Tuesday, 28 October 2025

ACCEPTED ON

Thursday, 11 December 2025

LICENSE



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

JOURNAL

"Environmental Economics"

ISSN PRINT

1998-6041

ISSN ONLINE

1998-605X

PUBLISHER

LLC “Consulting Publishing Company “Business Perspectives”

FOUNDER

LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

63



NUMBER OF FIGURES

3



NUMBER OF TABLES

4

© The author(s) 2025. This publication is an open access article.



BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Type of the article: Research Article

Received on: 28th of October, 2025

Accepted on: 11th of December, 2025

Published on: 17th of December, 2025

© Oxana Kirichok, Yuliia Orlovska,
Gulnara Zhanseitova, Alvena
Oriekhova, Denys Babaiev, Oleksii
Havrylenko, Tetiana Vasylieva, 2025

Oxana Kirichok, Ph.D. in Management,
Vice-rector, Caspian University,
Kazakhstan.

Yuliia Orlovska, Dr. of Economic Sc.,
Professor in International Economy,
Department of Economics and
International Economic Relation,
Ukrainian State University of Science
and Technology, Ukraine.

Gulnara Zhanseitova, Ph.D. in
Economics, Acting Associate Professor
of the Management Department,
Eurasian National University
named after Gumilyov, Kazakhstan.
(Corresponding author)

Alvena Oriekhova, Doctor of Science
(Economics), Professor, Head of the
Management Department named
after Professor L. Mykhailova, Sumy
National Agrarian University, Ukraine.

Denys Babaiev, M.B.A., CEO,
Co-founder, Scale Your Web LLC,
Philadelphia, PA, USA.

Oleksii Havrylenko, Ph.D., Postdoc,
Scientific Research Center for
Industrial Problems of Development
of the National Academy of Sciences of
Ukraine, Ukraine.

Tetiana Vasylieva, Dr., Prof., Research
Associate, Faculty of Business
Administration, Chair of Investment
and Finance, TU Bergakademie
Freiberg, Germany; Department
of Financial Technologies and
Entrepreneurship, Sumy State
University, Ukraine.



This is an Open Access article,
distributed under the terms of the
[Creative Commons Attribution 4.0
International license](https://creativecommons.org/licenses/by/4.0/), which permits
unrestricted re-use, distribution, and
reproduction in any medium, provided
the original work is properly cited.



Conflict of interest statement:

Author(s) reported no conflict of interest

Oxana Kirichok (Kazakhstan), Yuliia Orlovska (Ukraine), Gulnara Zhanseitova (Kazakhstan),
Alvena Oriekhova (Ukraine), Denys Babaiev (USA), Oleksii Havrylenko (Ukraine),
Tetiana Vasylieva (Germany, Ukraine)

BRIDGING DIGITAL INNOVATION AND ENERGY JUSTICE: THE ROLE OF ARTIFICIAL INTELLIGENCE IN ADVANCING ENERGY EQUITY

Abstract

Global progress toward universal access to affordable, reliable, and clean energy has stalled, with over two billion people still lacking access to clean cooking, and affordability pressures are rising. AI is emerging as an energy-intensive technology and a potential enabler of more equitable energy systems. This paper assesses whether AI vibrancy contributes to advancing energy equity across countries while accounting for differences in economic capacity. The study employs a balanced panel of 36 countries from 2017 to 2023 (252 observations), drawing on the Global AI Vibrancy Tool, World Bank Open Data, and the World Energy Council's Energy Trilemma Index. Box-Cox transformations were applied to address skewness, and panel econometric models (fixed and random effects) with robust standard errors were estimated. The FE model shows no significant within-country effect of AI vibrancy on energy equity ($R^2 = 0.012$). The RE model indicates a positive association: a one-unit increase in the AI vibrancy score results in an improvement of 0.00165 in the energy equity index ($p < 0.01$). At the same time, GDP per capita exerts a strong and highly significant effect ($p < 0.001$). The RE model explains 12.4% of the overall variation in energy equity. After correcting for heteroscedasticity and cross-sectional dependence, GDP per capita remains significant, whereas the effect of AI vibrancy weakens to marginal significance ($p \approx 0.09$). Country-specific effects further reveal systematic over- and under-performance beyond what AI vibrancy and income predict, underscoring the critical role of governance and institutional quality in shaping energy equity outcomes.

Keywords

sustainable energy systems, green digitalization, energy equity, artificial intelligence, AI vibrancy score, panel data, strategic management

JEL Classification

Q01, O42, O48, O33

INTRODUCTION

Ecological sustainability, progress toward the Sustainable Development Goals (SDG), and energy equity are deeply intertwined, as the distribution of clean, affordable, and reliable energy services determines both the environmental footprint of development and the fairness of its benefits and burdens. Energy systems worldwide are failing to deliver on the promise of SDG 7, with progress not only stalling but, in some cases, reversing, which makes the equity dimension newly urgent. The 2024 Tracking SDG 7 report warns that the world is off track on universal access; 2022 even saw a setback in electricity access after a decade of improvements, while around 2.1 billion people still lack access to clean cooking, resulting in severe health and gender impacts, including millions of premature deaths annually from household air pollution (IEA, 2024). UN SDG monitoring similarly identifies a clean-cooking deficit affecting ~2.1 billion people and projects that, without accelerated action, about 1.8 billion people could remain without clean cooking by 2030 (UNSD, 2024). In parallel, affordability

pressures since the 2022 price shock have strained households and public budgets, with the World Bank emphasizing that pricing and subsidy design are crucial for protecting individuals with low incomes while preserving fiscal space for investment in access (Akcura & Bloch, 2025). IMF estimates further underscore the scale of distortion: global fossil fuel subsidies reached USD 7 trillion (7.1% of world GDP) in 2022, complicating the equitable and efficient allocation of energy and public resources (Black et al., 2023).

Against this backdrop, artificial intelligence (AI) emerges as a double-edged but potentially enabling force for energy equity. The IEA's new Energy & AI analysis highlights AI's capacity to transform forecasting, grid operations, outage prevention, and demand response capabilities, which can lower system costs and improve reliability and affordability, especially in areas where variable renewables and distributed resources are growing (IEA, 2025). Complementary to IRENA (2019), it details how AI and digitalization unlock system flexibility and smart electrification across end-uses (transport, buildings, industry), supporting wider access at lower costs through innovations in enabling technologies, market design, and business models.

However, AI also raises new equity risks via its electricity demand, which data centers dominate. IEA scenarios suggest data-center power use could exceed 1,700 TWh by 2035 ($\approx 4.4\%$ of global electricity), intensifying grid constraints and affordability challenges if not matched by clean capacity, flexibility, and efficiency improvements (IEA, 2025). This tension strengthens the case for rigorous, evidence-based policy, targeting subsidies, investing in grids, storage, and digital infrastructure, and leveraging AI where it demonstrably reduces losses, improves service quality, and enables last-mile access. Empirically testing whether AI vibrancy correlates with better energy equity outcomes while controlling for income and correcting for data issues is timely and policyrelevant in light of these international assessments (World Bank, 2025).

In this context, investigating the role of AI in advancing energy equity becomes both timely and necessary. Global monitoring by the World Bank, the IMF, the IEA, and IRENA underscores that while universal access to affordable, reliable, and clean energy remains a critical challenge, emerging digital technologies, such as AI, offer new opportunities to address inefficiencies, reduce costs, and improve service delivery. At the same time, the rapid growth of AI itself raises concerns regarding energy demand, affordability, and equitable access. Understanding whether and how AI vibrancy contributes to enhancing energy equity across countries is essential for academic inquiry and informing policy strategies aimed at achieving Sustainable Development Goal 7. This study addresses this gap by empirically examining the interaction between AI development and energy equity in a cross-country panel framework.

1. LITERATURE REVIEW

Efforts to accelerate the ecological transition increasingly rely on AI as a key tool to reduce emissions, optimize the use of natural resources, and enable the large-scale integration of renewable energy sources. State-of-the-art assessments highlight how reduction curtailment, enhanced asset utilization, and decreased environmental footprint of energy production and consumption throughout the entire value chain can be achieved through AI-driven forecasting, optimization, and control (Ahmad et al., 2021; Liu et al., 2023; Khan et al., 2024). At the system level, AI embedded in smart grids, storage management, and demand

response is viewed as essential for unlocking the ecological potential of renewables while maintaining reliability and resilience (Ahmad et al., 2021; Bashynska et al., 2024; Kuzior et al., 2022). At the same time, public-sector and governance debates emphasize that these ecological benefits will materialize only if AI is integrated into policy and administrative practice in ways that protect the environment, uphold human dignity, and avoid new forms of ecological injustice (Androniceanu, 2024; Mura & Stehlíková, 2025).

Operational integration of renewables hinges on flexibility, with AI supporting short-term forecasting, optimal dispatch, and resilience of distributed

resources and buildings. Evidence suggests that AI-enabled controls can enhance reliability and occupant-centric efficiency in smart buildings, with spillover benefits for system-level flexibility and reduced environmental footprints (Liu et al., 2023). In microgrids, AI is combined with storage and electric vehicles to enhance energy management strategies, moderating variability from wind and solar sources and reducing curtailment and emissions (Khan et al., 2024). At the system margin, AI in global supply chains enhances energy security through predictive risk management, complementing the expansion of renewable energy and reducing exposure to disruptions linked to fossil fuels (Wang et al., 2025). These operational gains directly connect to equity by lowering costs and improving reliability for vulnerable users (Ahmad et al., 2021; Liu et al., 2023; Khan et al., 2024; Wang et al., 2025).

The diffusion of clean energy and green digital ventures depends on financeability, investor protection, and the ease of market entry, factors that determine whether AI tools translate into equitable and ecological outcomes. Barriers to credit and minority-investor protection impede clean and digital energy start-ups, while supportive tax compliance and streamlined registration materially improve survival and scale-up prospects (Artyukhov et al., 2024; Halynskiy et al., 2024; Lyeonov et al., 2025c; Oesterreich & Barej-Kaczmarek, 2024; Prokopenko et al., 2023). Investment risk in renewable energy entrepreneurship remains a central concern; however, AI-driven analytics can help mitigate this risk. Enabling policy and stable grid access are also decisive, including the basic prerequisite of reliable connections for European renewable energy start-ups (Dobrovolska et al., 2024; Lyeonov et al., 2025a). Regional cooperation initiatives frame AI and renewables as joint levers for integration and cross-border decarbonization, provided governance capacity is in place (Vakulenko & Rekunenko, 2025). Broader macro-institutional quality further conditions environmental outcomes, indicating that AI complements, rather than substitutes for, robust regulation (Mukhtarov et al., 2024). Fiscal instruments and market rules, such as gas storage levies or environmental tax reform, shape flows, prices, and fairness in cost burden, influencing equity along the renewable transition (Hudak et al., 2025; Kurbatova et al., 2023; Samusevych et al., 2024).

Urban sustainability agendas are increasingly relying on AI to manage demand, reduce waste, and foster circularity, delivering ecological co-benefits that align with energy justice. Smart-city analytics, including AI-augmented trend detection and smoothing, support targeted interventions in mobility, buildings, and distributed generation (Hrytsenko et al., 2024). AI in municipal waste management and industrial automation accelerates circular strategies, with further safety and environmental gains arising from AI-based risk detection at construction sites (Kajda & Karwot, 2025; Zaryczańska & Karwot, 2025). At the firm and supply chain levels, the “twin transformation” (digital plus circular) links AI, big data, and green logistics to improved sustainability performance and resource efficiency (Waqas et al., 2025). Consumer-facing AI (marketing analytics, engagement modelling, neuro-based message testing) can elevate energy awareness and promote pro-environmental behaviors, complementing technical decarbonization (Lazaroiu & Rogalska, 2024; Piwowarski, 2024; Glos & Karwot, 2025). Forecasts of sustainable consumption highlight the demand-side importance of renewable uptake and equitable cost distribution (Kontautienė et al., 2024).

Public-sector readiness determines whether AI delivers social and ecological dividends. Change management and civil service capability are repeatedly identified as prerequisites for responsible adoption, including in energy-relevant administrative processes (Barodi & Lalaoui, 2025). Digital transformation in finance and industry expands management control and sustainability tracking, but also raises implementation hurdles in heavy emitters such as petrochemicals, where AI can support cleaner operations if socio-economic challenges are addressed (El Massaoudi et al., 2025; Elmaghraby et al., 2025). Organizational work highlights AI’s contribution to resilient leadership and productivity, which enables the organizational bandwidth needed for deep renewable transitions (Ayu Gusti et al., 2024; Koldovskiy et al., 2025; Kozhakhmetova et al., 2024; Ibadildin et al., 2025). Ethical, privacy, and security concerns, spanning traffic enforcement, law enforcement use cases, social media data mining, and public anxieties, require explicit safeguards to prevent inequitable outcomes and reinforce legitimacy (Haley, 2025; Haley & Burrell, 2025; Wiczorek &

Postrzednik-Lotko, 2025; Yarovenko et al., 2024, 2025). Sector-specific risks in health and critical services underline the need to integrate cyber-resilience and sustainability criteria into AI governance (Sidii, 2024).

AI supports energy security by strengthening renewable-heavy systems and aligning ecological aims with reliability, while RES expansion in the EU shows that security assessments must incorporate renewable penetration and digital flexibility (Wang et al., 2025; Kuzior et al., 2025). Public interest and scholarly output on renewables, mapped via digital traces and bibliometrics, indicate growing societal and academic momentum, which AI can harness to accelerate just transitions (Lyeonov et al., 2025c). Citizen-facing interventions, including AI-informed environmental communication, influence waste sorting and green behaviors, suggesting a pathway for shared ownership of ecological goals (Lyeonov et al., 2025b). Adjacent domains, insurance acceptance among older adults, e-recruitment transparency, customer feedback analytics, and project-efficiency enhancement, demonstrate how AI normalizes digital participation and may reduce inclusion gaps relevant to energy justice (Chandran & Tholath, 2025; Pollifroni et al., 2025; Zakharchenko et al., 2025; Kildei et al., 2025; Kozhakhmetova et al., 2024). Entrepreneurship ecosystems, cyber-insurance in Agriculture 4.0, and knowledge economy development further contextualize how risk transfer, innovation, and local capacity intersect with green and digital agendas (Sitnicki et al., 2024a; Sitnicki et al., 2024b; Kritikos et al., 2025; S. Kumar & J. Kumar, 2024). Geopolitical dynamics shape access to technology and supply-chain resilience, implying that AI-enabled energy justice is also contingent upon strategic conditions in contested regions (Ahmed, 2025).

The literature converges on AI as a system-level enabler of ecological performance and renewable integration, with tangible gains in flexibility, reliability, and consumer engagement when aligned with robust institutions and ethical safeguards (Ahmad et al., 2021; Liu et al., 2023; Khan et al., 2024; Waqas et al., 2025). At the same time, financial, regulatory, and organizational prerequisites condition whether these

digital efficiencies translate into equitable access and fair cost burdens across households and firms (Artyukhov et al., 2024; Dobrovolska et al., 2024; Halynskiy et al., 2024; Hudak et al., 2025). Overall, bridging digital innovation and energy justice depends on coupling AI with credible governance, inclusive finance, and citizen-centered engagement so that renewable expansion delivers both ecological gains and distributive fairness (Kuzior et al., 2025; Lyeonov et al., 2025a; Mura & Stehlíková, 2025).

The literature demonstrates that AI can play an enabling role in advancing energy equity by facilitating clean energy transitions, improving the resilience and inclusiveness of energy systems, and supporting governance and consumer engagement. However, the evidence also highlights that AI's potential is contingent on strong institutional frameworks, ethical safeguards, and complementary socio-economic policies. This underscores the importance of empirical research that examines the extent to which AI vibrancy translates into measurable improvements in energy equity across countries.

This study aims to empirically investigate the relationship between artificial intelligence vibrancy and energy equity in a panel of countries, using GDP per capita as a control for economic capacity.

2. METHODOLOGY

2.1. Data sources

The analysis combines three internationally recognized databases:

- Dependent variable – Energy Equity – is drawn from the World Energy Council's Energy Trilemma Index (World Energy Council, n.d.). The Energy Equity dimension evaluates a country's capacity to provide universal access to reliable, affordable, and abundant energy for households and businesses, encompassing indicators such as access to electricity and clean cooking fuels, energy consumption that fosters prosperity, and the affordability of energy services.

- Predictor – AI Vibrancy – data are obtained from the Global AI Vibrancy Tool developed by Stanford University’s Human-Centred Artificial Intelligence Institute (Stanford University, n.d.). The tool provides a multidimensional index capturing AI activity across research, investment, and talent indicators, reflecting national AI development and adoption capabilities.
- GDP per capita is a proxy for economic capacity, and GDP per capita (constant 2015 USD) is sourced from the World Bank Open Data platform (World Bank, n.d.). This control variable accounts for structural differences in income levels that may influence the provision of equitable energy access.

2.2. Panel construction

The study constructs a balanced panel of 36 countries observed over the period 2017–2023, yielding a total of 252 observations. Data were harmonized across sources and processed in R Studio. Box-Cox transformations were applied to address the strong skewness in the raw distributions of AI vibrancy and energy equity, ensuring that the data conformed more closely to the assumptions of linear regression analysis. Descriptive statistics were computed to characterize the dataset prior to estimation.

The coverage of the Global AI Vibrancy Tool database restricts the sample of countries in this study. As a result, the analysis includes 36 economies: Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Estonia, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, Luxembourg, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Saudi Arabia, Singapore, Spain, South Africa, South Korea, Sweden, Switzerland, Turkey, the United Arab Emirates, the United Kingdom, and the United States. The Global AI Vibrancy Tool was selected as the primary data source for AI measurement because it provides the longest consistent time series (2017–2023) across a wide range of countries, enabling the construction of a balanced panel dataset suitable for econometric analysis.

2.3. Empirical strategy

The study employs a panel econometric framework to examine the relationship between AI vibrancy and energy equity across countries, controlling for the role of economic development. The empirical specification is expressed as:

$$\begin{aligned} \text{EnergyEquity}_{it} = & \alpha + \beta_1 \text{AIVibrancy}_{it} \\ & + \beta_2 \text{GDPpc}_{it} + \mu_i + \varepsilon_{it}, \end{aligned} \quad (1)$$

where EnergyEquity_{it} is the energy equity index of country i at time t , AIVibrancy_{it} measures AI-related activity and capacity, and GDPpc_{it} denotes GDP per capita (in constant 2015 US dollars). The term μ_i captures unobserved country-specific effects, while ε_{it} is the idiosyncratic error.

Two model specifications are considered. The fixed effects (FE) model controls for unobserved time-invariant heterogeneity, capturing within-country variation. The random effects (RE) model utilizes both within- and between-country variation but assumes that unobserved effects are uncorrelated with the regressors. The Hausman test guides model choice. Given evidence of heteroscedasticity and cross-sectional dependence in the residuals, robust inference is conducted using heteroscedasticity-consistent and Driscoll-Kraay standard errors.

3. RESULTS

The descriptive statistics reveal substantial variation in the dataset across the three main variables. The Vibrancy Score (x1) exhibits a high standard deviation (85.63) compared to its mean (18.46), with extreme maximum values reaching 1363.0. The strong positive skewness (15.36) and extremely high kurtosis (238.22) indicate the presence of severe outliers and a highly non-normal distribution. This suggests that while most countries or cases record relatively low vibrancy scores, a few observations display disproportionately high values, which can significantly affect regression estimates if not correctly accounted for. Transformation might therefore be necessary to normalize the distribution.

The GDP per capita (x2) variable is widespread, ranging from 1,788.70 to 110,425.9 (constant 2015 USD). Although the mean (39,151.71) and median

(40,501.44) are relatively close, the distribution exhibits slight positive skewness (0.68), indicating that a few high-income economies tend to pull the distribution upward. Nevertheless, its kurtosis value (0.18) indicates a distribution not heavily influenced by extreme outliers.

The Energy Equity Index (y), similar to the Vibrancy Score, also exhibits severe non-normality. Its mean (123.07) is heavily influenced by extreme outliers, given the maximum of 8,711.0 and a relatively small median (95.06). Both skewness (15.67) and kurtosis (244.73) confirm a highly skewed and heavy-tailed distribution. This may imply that most economies have clustered moderate equity scores, while a few register extraordinarily high values, again necessitating transformation before econometric analysis.

The statistics suggest that while GDP per capita is relatively stable across countries, both Vibrancy Score and Energy Equity Index display extreme outliers and heavy skewness. Addressing these distributional properties will be crucial for ensuring robust econometric results.

The Box–Cox procedure estimated the optimal transformation parameter as $\lambda = -0.71$, with a 95% confidence interval of -1 to 0 . This indicates that the original dependent variable is highly skewed and departs significantly from normality. A negative λ implies that reciprocal-type transformations are most suitable for stabilizing variance and improving the normal distribution of residuals. Specifically, $\lambda = -0.71$ lies between the conventional reciprocal transformation ($\lambda = -1$) and the log transformation ($\lambda = 0$). This suggests that the data require a strong variance-stabilizing adjustment, though not as extreme as a full reciprocal.

The Box–Cox likelihood profile (Figure 1) supports this conclusion. The curve reaches its maximum log-likelihood around $\lambda \approx -0.71$, while the 95% confidence interval (bounded by vertical dashed lines) excludes $\lambda = 1$, indicating that no transformation (raw scale) would be inappropriate. The fact that $\lambda = 0$ (logarithmic transformation) lies within or close to the confidence interval suggests that a log transformation could be considered a practical alternative. However, the estimated λ provides the most statistically efficient adjustment.

In practical terms, applying this transformation reduces the influence of extreme outliers and heavy skewness in the dependent variable, leading to more reliable regression estimates and improved compliance with the assumptions of linear modelling.

The Box–Cox analysis for the Vibrancy Score ($x1$) estimated an optimal λ of -0.02 , with the 95% confidence interval encompassing $\lambda = 0$. This result suggests that the data are best approximated by a transformation close to the natural logarithm. Since the estimated λ lies extremely close to zero, a log transformation provides a statistically valid and practically convenient approach.

The likelihood profile shown in Figure 2 supports this interpretation. The maximum log-likelihood occurs near $\lambda = -0.02$, while the confidence band around the peak includes $\lambda = 0$, confirming that the logarithmic specification is an acceptable simplification. Unlike the case of y , where a strongly negative λ was preferred, the distribution of $x1$ requires only a mild correction. Applying the log transformation is expected to reduce the heavy right skewness observed in the raw variable and improve its suitability for regression modelling by stabilizing variance and approximating normality.

Table 1. Descriptive statistics of variables

Variable	Vibrancy Score ($x1$)	GDP per capita (constant 2015 USD) ($x2$)	Energy Equity Index (y)
Obs. (n)	252	252	252
Mean	18.46	39,151.71	123.07
Std. Dev.	85.63	24,860.40	543.3
Median	11.18	40,501.44	95.06
Min	0.34	1,788.70	38.63
Max	1363	110,425.9	8711
Range	1,362.66	108,637.19	8,672.37
Skewness	15.36	0.68	15.67
Kurtosis	238.22	0.18	244.73

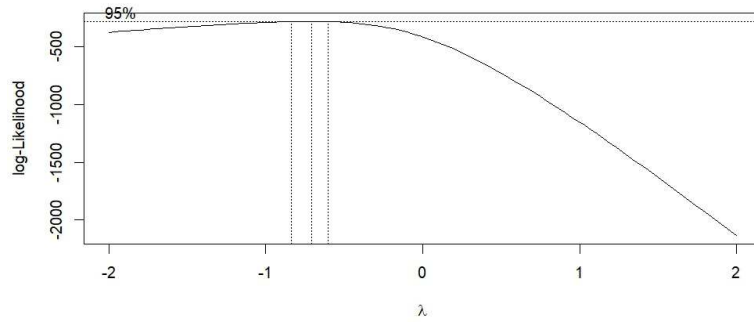


Figure 1. The Box-Cox likelihood profile for y

The Box-Cox analysis for the Vibrancy Score ($x1$) estimated an optimal λ of -0.02 , with the 95% confidence interval encompassing $\lambda = 0$. This result suggests that the data are best approximated by a transformation close to the natural logarithm. Since the estimated λ lies extremely close to zero, a log transformation provides a statistically valid and practically convenient approach.

The likelihood profile shown in Figure 2 supports this interpretation. The maximum log-likelihood occurs near $\lambda = -0.02$, while the confidence band around the peak includes $\lambda = 0$, confirming that the logarithmic specification is an acceptable simplification. Unlike the case of y , where a strongly negative λ was preferred, the distribution of $x1$ requires only a mild correction. Applying the log transformation is expected to reduce the heavy right skewness observed in the raw variable and improve its suitability for regression modelling by stabilizing variance and approximating normality.

The histograms in Figure 3 demonstrate the effect of Box-Cox transformations on the Vibrancy Score

($x1$) and the Energy Equity Index (y). In their original form, both variables exhibit strong right skewness, with most observations concentrated at the lower end of the distribution and a small number of extreme outliers driving long upper tails. This is consistent with the high skewness and kurtosis values reported in the descriptive statistics.

After transformation, the distributions of both variables become notably more symmetric. For $x1$, the log-type transformation ($\lambda \approx 0$) successfully compresses the scale, reducing the influence of extreme values and producing an approximately bell-shaped distribution centered between 2 and 4. For y , the reciprocal-type transformation ($\lambda \approx -0.71$) similarly reduces skewness, clustering most values within a much narrower range (1.33–1.37) compared to the raw scale. Although the transformed y variable remains tightly concentrated, the distribution is significantly closer to normality than the original.

The Box-Cox procedure stabilizes variance and reduces non-normality for both indicators. This adjustment is essential for ensuring that subse-

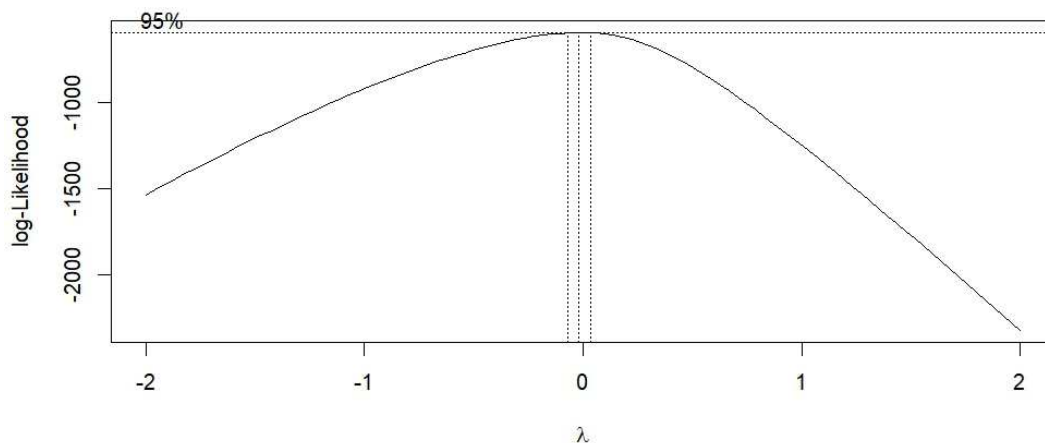


Figure 2. The Box-Cox likelihood profile for $x1$

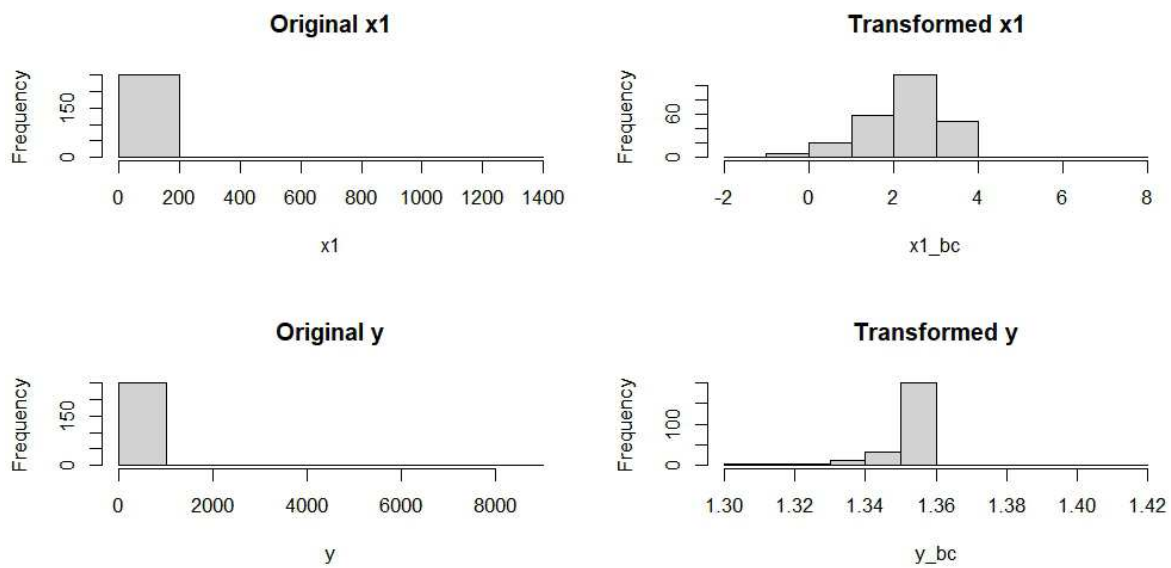


Figure 3. The effect of applying Box–Cox transformations to the Vibrancy Score (x1) and the Energy Equity Index (y)

quent regression modelling satisfies the standard assumptions of linearity, homoscedasticity, and normally distributed residuals.

The FE (within) model indicates that neither the Vibrancy Score (x1_bc) nor GDP per capita (x2) significantly explains variation in the transformed Energy Equity Index (y_bc) after controlling for time-invariant heterogeneity across countries. The coefficients are small in magnitude, with *p*-values far above conventional significance levels (*p* = 0.1185 for x1_bc and *p* = 0.4625 for x2). The explanatory power is weak, as shown by an *R*-squared of 0.012, and the *F*-statistic fails to reject the null hypothesis that the independent variables jointly have no explanatory power (*p* = 0.267). This suggests that within-country temporal variation in vibrancy and income levels does not substantially

account for changes in energy equity after removing unobserved country characteristics.

In contrast, the RE model yields statistically significant results. Both Vibrancy Score (x1_bc) and GDP per capita (x2) are positively associated with the Energy Equity Index at high levels of statistical significance (*p* < 0.01). The estimated coefficients imply that a marginal increase in vibrancy and income is associated with measurable improvements in energy equity across the panel. The *R*-squared (0.124) indicates moderate explanatory power, and the model passes the joint significance test (Chi-sq = 35.26, *p* < 0.001).

The apparent contrast between the RE and FE estimates arises from how the two estimators exploit variation in the data. The RE model utilizes between-country variation (cross-sectional differ-

Table 2. Fixed effects and random effects estimates for Energy Equity Index

Variable	FE model				RE model			
	FE Estimate	Std. Error	t-value	p-value	RE Estimate	Std. Error	z-value	p-value
Intercept	–	–	–	–	1.3439	0.0020	672.27	< 0.0001***
Vibrancy Score (x1_bc)	0.00094	0.00060	1.57	0.119	0.00165	0.00056	2.95	0.003**
GDP per capita (x2)	< 0.0001	< 0.0001	0.74	0.463	< 0.0001	< 0.0001	4.06	< 0.0001***
R-squared	0.0123				0.1240			
Adjusted R-squared	–0.1585				0.1170			
F-test / Chi-sq	F = 1.33 (p = 0.267)				χ ² = 35.26 (p < 0.001)			

Note: ‘***’ – 0.001; ‘**’ – 0.01; ‘*’ – 0.05; ‘.’ – 0.1; ‘no symbol’ – insignificant.

ences across units) and within-country variation (changes over time within the same unit). Since energy equity, GDP per capita, and vibrancy scores display substantial structural differences across countries, for example, more prosperous economies systematically record higher equity scores, the RE estimator captures this cross-sectional signal and produces statistically significant results.

By contrast, the FE model removes all time-invariant country-specific effects and relies exclusively on within-country temporal variation. Once these fixed characteristics are differenced, the remaining year-to-year changes in GDP per capita and vibrancy scores are relatively modest compared to the significant structural disparities between countries. Consequently, the coefficients lose statistical power, making the FE results insignificant. This does not imply that no relationship exists, but instead that the explanatory strength is primarily driven by persistent cross-country heterogeneity rather than short-term within-country dynamics.

The Breusch-Pagan test for heteroscedasticity yields a statistically significant result (BP = 8.99, $p = 0.011$). This indicates that the assumption of homoscedasticity is violated, suggesting that the variance of the residuals is not constant across observations. In the context of panel data, specific units contribute disproportionately to the overall error structure, potentially biasing the conventional standard errors of the estimated coefficients. Robust variance-covariance estimators are therefore required to correct for this heteroscedasticity.

The Wooldridge/Breusch-Godfrey test for serial correlation in the idiosyncratic errors does not re-

ject the null hypothesis ($\chi^2 = 1.33$, $p = 0.988$). This implies no evidence of serial correlation in the within-unit residuals over time, suggesting that temporal dependence is not a concern for the RE specification.

The tests for cross-sectional dependence provide mixed evidence. The Breusch-Pagan LM test is highly significant ($\chi^2 = 893.04$, $p < 0.001$), indicating a strong correlation of residuals across cross-sectional units. This is not surprising in macro-panel settings, where countries may be simultaneously affected by global shocks or regional spillovers. However, the Pesaran CD test, which is more appropriate for panels with many cross-sectional units and smaller time dimensions, does not indicate significant cross-sectional dependence ($z = -0.63$, $p = 0.531$). Given the relatively balanced panel size (36 countries over 7 years), the LM test result is more likely to be informative, highlighting the need to account for contemporaneous correlation between units.

These results suggest that while the RE model does not suffer from autocorrelation, it is affected by heteroscedasticity and cross-sectional dependence. Consequently, inference based on conventional standard errors would be misleading, and robust estimators such as Driscoll-Kraay or cluster-robust standard errors are recommended to ensure reliable hypothesis testing and coefficient significance.

The analysis highlights a nuanced interaction between AI vibrancy and energy equity. At the same time, the econometric results show only weak evidence of a direct within-country effect of AI vi-

Table 3. RE model with robust standard errors

Variable	Estimate	Robust SE (HC1, Clustered)	t-value	p-value	Robust SE (Driscoll-Kraay)	t-value	p-value
Intercept	1.3439	0.00383	350.91	< 0.0001***	0.00305	440.41	< 0.0001***
Vibrancy Score (x1_bc)	0.00165	0.00095	1.74	0.083	0.00098	1.69	0.093
GDP per capita (x2)	< 0.0001	< 0.0001	3.05	0.003**	< 0.0001	4.69	< 0.0001***
N (Obs.)				252			
Individuals (n)				36			
Time periods (T)				7			
R-squared (overall)				0.124			

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant. HC1 standard errors are heteroscedasticity-robust and clustered at the individual level. Driscoll-Kraay standard errors are robust to heteroscedasticity, serial correlation, and cross-sectional dependence.

brancy on the Energy Equity Index; the consistently positive association across specifications highlights the potential for AI-driven innovations to support equitable energy access. Energy equity, defined as a country's ability to provide universal access to reliable, affordable, and abundant energy, encompasses both basic needs, such as access to electricity and clean cooking fuels, and prosperity-enabling dimensions, including sufficient energy for domestic and commercial use. In this context, AI applications in demand forecasting, smart grids, predictive maintenance, and pricing mechanisms may reduce inefficiencies and improve affordability, thereby indirectly strengthening the equity dimension of energy systems.

At the same time, the findings confirm the central role of economic capacity, as measured by GDP per capita, in determining energy equity outcomes. Wealthier economies have greater financial and institutional resources to expand infrastructure, subsidize access, and invest in advanced technologies such as AI-enabled energy management. This implies that AI alone cannot bridge the equity gap unless embedded in broader structural transformations supported by adequate economic development. For lower- and middle-income countries, targeted policies combining AI deployment with investments in affordability, clean technologies,

and access-oriented infrastructure are essential. Ultimately, the interplay between AI and energy equity is not merely technological but socio-economic: AI can act as an enabling instrument, but its effectiveness depends on a country's underlying capacity to integrate innovations into equitable and inclusive energy strategies.

The country-specific effects (Table 4) represent the random intercepts from the random effects model, that is, systematic deviations of each country's average (transformed) energy equity from the overall panel mean after controlling for AI vibrancy and GDP per capita. Positive values of indicate that, given the same levels of AI vibrancy and income, a country tends to achieve higher-than-average energy equity. At the same time, negative values indicate lower-than-average energy equity. The magnitudes are small because they are expressed on the Box-Cox-transformed scale of the Energy Equity Index, where the overall variation is already compressed.

Interpreting the pattern, several countries stand out. Portugal (0.0104), Saudi Arabia (0.0078), Estonia (0.0055), Poland (0.0044), Spain (0.0048), the United Arab Emirates (0.0042), and New Zealand (0.0031) show relatively high positive country effects, suggesting that their institutional,

Table 4. Estimated country effects from the random effects model

No.	Country	Random Effect (u _i)	No.	Country	Random Effect (u _i)
1	Australia	0.0003987	19	Mexico	-0.0043379
2	Austria	0.0025710	20	Netherlands	0.0012771
3	Belgium	0.0028460	21	New Zealand	0.0031263
4	Brazil	-0.0063121	22	Norway	-0.0030432
5	Canada	0.0021890	23	Poland	0.0044188
6	China	0.0026647	24	Portugal	0.0104050
7	Denmark	0.0002959	25	Russia	-0.0003296
8	Estonia	0.0054759	26	Saudi Arabia	0.0077540
9	Finland	0.0008257	27	Singapore	-0.0024334
10	France	0.0036392	28	South Africa	-0.0117508
11	Germany	0.0028360	29	South Korea	0.0026988
12	India	-0.0275297	30	Spain	0.0047906
13	Ireland	-0.0037045	31	Sweden	0.0002330
14	Israel	0.0028726	32	Switzerland	-0.0042513
15	Italy	0.0030087	33	Turkey	-0.0009006
16	Japan	0.0029198	34	United Arab Emirates	0.0042359
17	Luxembourg	-0.0072061	35	United Kingdom	0.0017492
18	Malaysia	-0.0006685	36	United States	-0.0007641

Note: Values represent estimated random intercepts from the Random Effects model. Positive values indicate above-average country performance in energy equity after controlling for AI vibrancy and GDP per capita. Negative values indicate below-average performance. All values are reported on the Box-Cox-transformed scale of the Energy Equity Index.

regulatory, or structural conditions allow them to deliver slightly better energy equity than would be expected purely from AI vibrancy and GDP levels. By contrast, India (-0.0275) and South Africa (-0.0118) exhibit the most negative effects, indicating systematic underperformance in energy equity relative to their AI and income characteristics. At the same time, Brazil, Luxembourg, Switzerland, Mexico, and Norway also display modest negative deviations. For most advanced economies (e.g., Germany, France, Japan, Canada, Sweden), the effects are small and close to zero, implying that performance is broadly in line with model predictions and that there is limited additional country-specific advantage or disadvantage once AI and income are taken into account.

4. DISCUSSION

The empirical results reveal a complex and uneven relationship between AI vibrancy and energy equity. The fixed effects model suggests that there is no statistically significant within-country effect of AI vibrancy on energy equity. In contrast, the random effects model reveals a positive association, though this relationship becomes weaker when robust standard errors are applied. By contrast, GDP per capita emerges as a consistently strong determinant of equity outcomes across specifications. These findings suggest that the explanatory power of AI vibrancy lies more in cross-country differences than in short-term within-country changes, highlighting the structural dependence of energy equity on broader economic development.

This conclusion aligns with previous scholarship emphasizing the foundational role of institutional and financial capacity in enabling equitable energy transitions. Studies on clean and digital energy start-ups underline that access to credit, supportive regulatory environments, and institutional quality remain critical enablers of innovation and equitable outcomes (Artyukhov et al., 2024; Halynskiy et al., 2024; Mukhtarov et al., 2024). The absence of significant within-country effects in the fixed-effects model mirrors the challenges identified in these works, as short-term dynamics of AI adoption alone are insufficient to drive equity without systemic institutional support.

The results further align with evidence that income levels have a significant influence on energy equity. Research on energy poverty, sustainable consumption, and consumer satisfaction confirms that economic development conditions affordability and access to energy services (Oesterreich & Barej-Kaczmarek, 2024; Kontautienė et al., 2024; Li et al., 2022). This consistency across empirical and conceptual findings suggests that while AI may improve system efficiency and governance, its impact on equity remains contingent upon the economic resources available to support infrastructure and affordability measures.

Nonetheless, the positive associations observed in the random effects model provide support for the view that AI can act as an enabling instrument when structural conditions are favorable. Literature on smart cities, circular economy transformations, and sustainable business leadership suggests that AI has the capacity to enhance resilience, optimize service provision, and strengthen pro-environmental behaviors (Hrytsenko et al., 2024; Waqas et al., 2025; Koldovsky et al., 2025). These findings align with the positive coefficients in the RE model, which suggest that countries with stronger AI ecosystems and higher income levels are better positioned to translate digital innovation into equitable energy outcomes.

At the same time, the weakened significance of AI vibrancy under robust standard errors reflects the concerns raised in studies on ethical risks, institutional readiness, and socio-economic disparities in digitalization. Evidence on bias in AI systems, civil servants' preparedness, and ethical dilemmas in traffic enforcement reinforces the need for governance frameworks that prevent technological adoption from reproducing inequalities (Haley, 2025; Barodi & Lalaoui, 2025; Mura & Stehlíková, 2025). The econometric findings thus support the argument that without deliberate policies and governance safeguards, AI's potential contribution to energy equity will remain limited.

The study contributes to the literature by demonstrating that AI vibrancy has a positive but modest relationship with energy equity across countries, confirming broader findings that technological innovation is most effective when embedded in supportive institutional and economic contexts.

These results underscore the need to frame AI not as a stand-alone solution but as part of a wider socio-economic and policy framework aimed at achieving equitable and sustainable energy systems.

Despite its contributions, this paper is subject to several limitations. First, the sample is restricted to the 36 countries covered by the Global AI Vibrancy Tool, which excludes many developing economies where energy equity challenges are most acute, thereby limiting the generalizability of the findings. Second, the dataset period (2017–2023) is relatively short for panel econometric analysis, reducing the ability to capture

long-term dynamics between AI development and energy equity. Third, both AI vibrancy and energy equity are measured through composite indices, which, although comprehensive, may mask important sectoral or regional disparities within countries. Fourth, the study does not explicitly address potential endogeneity between AI adoption and energy equity, relying instead on robustness checks to mitigate bias. Finally, the analysis is constrained by data availability. It does not incorporate complementary factors such as institutional quality, regulatory frameworks, or investment in energy infrastructure, which may also shape the nexus between AI and equitable energy access.

CONCLUSION

This study aimed to empirically assess whether AI vibrancy contributes to advancing energy equity across countries while accounting for differences in economic capacity.

The econometric results indicate a nuanced role of AI vibrancy in shaping energy equity. The FE model, based on within-country variation, finds no significant effect of either AI vibrancy or GDP per capita on energy equity. In contrast, the RE model, which utilizes both cross-country and temporal variation, reveals positive and significant effects for both variables (AI vibrancy: +0.00165 on the equity index, $p < 0.01$; GDP per capita: $p < 0.001$; $R^2 = 0.124$). After correcting for heteroscedasticity and cross-sectional dependence, GDP per capita remains strongly significant. At the same time, the effect of AI vibrancy falls to marginal significance ($p \approx 0.09$), suggesting that economic development is the primary driver of energy equity, with AI vibrancy playing a supportive but secondary role. Country-specific effects further reveal that some countries systematically over- or underperform relative to their AI vibrancy and income, underscoring the importance of governance quality and energy institutions in translating technological and economic capacity into fair and sustainable energy access.

From a policy perspective, the results highlight several priorities. First, economic capacity remains the strongest predictor of energy equity, underscoring the need for inclusive growth strategies that expand fiscal space for infrastructure and access investments. Second, AI should be regarded as a complementary enabler rather than a substitute for traditional drivers of energy equity. Policymakers should focus on targeted applications of AI in energy forecasting, grid optimization, outage prevention, and demand-side management, where cost reductions and efficiency gains can directly enhance affordability and reliability. Third, robust governance frameworks are required to mitigate risks linked to AI's energy demand, particularly the rapid expansion of data centers that could consume over 1,700 TWh by 2035 if left unchecked. Therefore, investment in clean capacity, smart grids, and storage solutions is critical to ensure that AI adoption does not undermine equity objectives. Finally, international cooperation is essential to support lower- and middle-income countries, combining the deployment of AI with concessional financing, technology transfer, and capacity building to extend equitable access to energy.

The study demonstrates that AI can play a significant role in promoting energy equity, but its impact depends on broader structural and economic factors. Harnessing AI's potential requires deliberate integration into national energy strategies, with equity as a guiding principle alongside efficiency and sustainability.

AUTHOR CONTRIBUTIONS

Conceptualization: Oxana Kirichok, Yuliia Orlovska, Gulnara Zhanseitova, Alvina Oriekhova, Denys Babaiev, Oleksii Havrylenko, Tetiana Vasylieva.

Data curation: Oleksii Havrylenko.

Formal analysis: Oleksii Havrylenko.

Funding acquisition: Yuliia Orlovska.

Investigation: Oleksii Havrylenko.

Methodology: Oleksii Havrylenko.

Project administration: Tetiana Vasylieva.

Resources: Oxana Kirichok.

Software: Denys Babaiev, Oleksii Havrylenko.

Supervision: Tetiana Vasylieva.

Validation: Alvina Oriekhova, Oleksii Havrylenko.

Visualization: Gulnara Zhanseitova, Oleksii Havrylenko.

Writing – original draft: Oxana Kirichok, Yuliia Orlovska, Gulnara Zhanseitova, Alvina Oriekhova, Denys Babaiev, Oleksii Havrylenko, Tetiana Vasylieva.

Writing – review & editing: Oxana Kirichok, Yuliia Orlovska, Gulnara Zhanseitova, Alvina Oriekhova, Denys Babaiev, Oleksii Havrylenko, Tetiana Vasylieva.

ACKNOWLEDGMENT



The article was prepared as a part of the MSCA4Ukraine project 06030419, European Union's Horizon 2020 Research and Innovation Programme. Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union, the European Research Executive Agency, or the MSCA4Ukraine Consortium. Neither the European Union nor the European Research Executive Agency, nor the MSCA4Ukraine Consortium as a whole, nor any individual member institutions of the MSCA4Ukraine Consortium can be held responsible for them.

REFERENCES

1. Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in the sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*, 289, Article 125834. <https://doi.org/10.1016/j.jclepro.2021.125834>
2. Ahmed, S. (2025). The US strategy of multidomain containment and China's counter-responses in the Indo-Pacific (2019–2025). *Geopolitics under Globalization*, 6(1), 45-58. [https://doi.org/10.21511/gg.06\(1\).2025.05](https://doi.org/10.21511/gg.06(1).2025.05)
3. Akcura, E., & Bloch, F. C. (2025, May 19). *The high price of cheap fuel: What new global data reveals about liquid fuel subsidies*. World Bank Blogs. Retrieved from <https://blogs.worldbank.org/en/opensource/the-high-price-of-cheap-fuel--what-new-global-data-reveals-about>
4. Androniceanu, A. (2024). Generative artificial intelligence, present and perspectives in public administration. *Administratie si Management Public*, 43(43), 105-119. <https://doi.org/10.24818/amp/2024.43-06>
5. Artyukhov, A., Havrylenko, O., Churikanova, O., & Mohylina, K. (2024). Overcoming barriers to developing clean and digital energy start-ups: Access to credit and protection of minority investors' rights. *Financial Markets, Institutions and Risks*, 8(4), 226-248. [https://doi.org/10.61093/fmir.8\(4\).226-248.2024](https://doi.org/10.61093/fmir.8(4).226-248.2024)
6. Ayu Gusti, M., Satrianto, A., Candrianto, Juniardi, E., & Fitra, H. (2024). Artificial intelligence for employee engagement and productivity. *Problems and Perspectives in Management*, 22(3), 174-184. [https://doi.org/10.21511/ppm.22\(3\).2024.14](https://doi.org/10.21511/ppm.22(3).2024.14)
7. Barodi, M., & Lalaoui, S. (2025). Civil servants' readiness for AI adoption: The role of change management in Morocco's public sector. *Problems and Perspectives in Management*, 23(1), 63-75. [https://doi.org/10.21511/ppm.23\(1\).2025.05](https://doi.org/10.21511/ppm.23(1).2025.05)
8. Bashynska, I., Kryvda, V., Sala, D., Niekrasova, L., Maksymov, O., & Suvorov, V. (2024). Simulation model of a unified energy system for different scenarios of planned disturbances. *Energies*, 17(23), Article 6136. <https://doi.org/10.3390/en17236136>

9. Black, S., Liu, A.A., Parry I.W.H., & Vernon, N. (2023). *IMF Fossil Fuel Subsidies Data: 2023 Update* (IMF Working Papers 2023, 169). International Monetary Fund. <https://doi.org/10.5089/9798400249006.001>
10. Chandran, K. R. P., & Ittimani Tholath, D. (2025). Digital insurance acceptance among older adults in the context of AI. *Insurance Markets and Companies*, 16(1), 131-145. [https://doi.org/10.21511/ins.16\(1\).2025.11](https://doi.org/10.21511/ins.16(1).2025.11)
11. Dobrovol'ska, O., Ortmanns, W., Podossynnikov, S., Halyn'skyi, D., & Miniailo, A. (2024). Start-ups and entrepreneurship in renewable energy: Investments and risks. *Financial Markets, Institutions and Risks*, 8(2), 213-240. [https://doi.org/10.61093/fmir.8\(2\).213-240.2024](https://doi.org/10.61093/fmir.8(2).213-240.2024)
12. El Massaoudi, E.M., El Hammoumi, A., Seghyar, N., & El Ouali, A. (2025). Digital transformation and improvement of management control: Empirical study in financial institutions. *Investment Management and Financial Innovations*, 22(3), 455-469. [https://doi.org/10.21511/imfi.22\(3\).2025.34](https://doi.org/10.21511/imfi.22(3).2025.34)
13. Elmaghraby, I., Khourshed, N. F., Ragheb, M. A., & Beshr, M. H. (2025). Studying the requirements and socioeconomic challenges of digitalization on sustainability: An applied study in the petrochemical industry. *SocioEconomic Challenges*, 9(2), 21-39. [https://doi.org/10.61093/sec.9\(2\).21-39.2025](https://doi.org/10.61093/sec.9(2).21-39.2025)
14. Glos, J., & Karwot, J. (2025). Study of customer attitudes toward AI-driven solutions in customer support services. *Knowledge Economy and Lifelong Learning*, 1(2), 24-49. [https://doi.org/10.61093/kell.1\(2\).24-49.2025](https://doi.org/10.61093/kell.1(2).24-49.2025)
15. Haley, P. (2025). Artificial intelligence and ethical dimensions of automated traffic enforcement: Implications for public health, healthcare equity, and social justice. *Health Economics and Management Review*, 6(2), 32-49. <https://doi.org/10.61093/hem.2025.2-03>
16. Haley, P., & Burrell, D. N. (2025). Integrating artificial intelligence into law enforcement: Socioeconomic and ethical challenges. *SocioEconomic Challenges*, 9(2), 60-77. [https://doi.org/10.61093/sec.9\(2\).60-77.2025](https://doi.org/10.61093/sec.9(2).60-77.2025)
17. Halyn'skyi, D., Lytiuha, Y., & Telizhenko, O. (2024). The impact of tax burden payment indicators and ease of tax compliance on the development of clean and digital energy startups. *Financial Markets, Institutions and Risks*, 8(4), 204-225. [https://doi.org/10.61093/fmir.8\(4\).204-225.2024](https://doi.org/10.61093/fmir.8(4).204-225.2024)
18. Hrytsenko, L., Krawczyk, D., Derkach, L., & Kolomiets, S. (2024). The role of smart city in achieving sustainable development: Google Trends analysis and exponential time series smoothing models. *Business Ethics and Leadership*, 8(1), 190-202. [https://doi.org/10.61093/bel.8\(1\).190-202.2024](https://doi.org/10.61093/bel.8(1).190-202.2024)
19. Hudak, M., Čermáková, K., Kadeřábková, B., & Popescu, I.A. (2025). Policy analysis of the German gas storage levy at cross-border points: Implications for flows, prices, and regional market integration. *Economics and Sociology*, 18(2), 246-270. <https://doi.org/10.14254/2071-789X.2025/18-2/13>
20. Ibadildin, N., Kenzhin, Z., Yeshenkulova, G., Ismailova, R., Nurguzhina, A., Nassanbekova, S., & Kadyrova, A. (2025). Artificial intelligence in project management: A bibliometric analysis. *Problems and Perspectives in Management*, 23(2), 252-264. [https://doi.org/10.21511/ppm.23\(2\).2025.17](https://doi.org/10.21511/ppm.23(2).2025.17)
21. IEA. (2024). *Tracking SDG7: The Energy Progress Report, 2024*. Washington, DC: IEA, IRENA, UNSD, World Bank, WHO. Retrieved from <https://www.iea.org/reports/tracking-sdg7-the-energy-progress-report-2024>
22. IEA. (2025). *Energy and AI* (IEA World Energy Outlook Special Report). Paris: International Energy Agency Directorate of Sustainability, Technology and Outlooks. Retrieved from <https://iea.blob.core.windows.net/assets/40a4db21-2225-42f0-8a07-addcc2ea86b3/EnergyandAI.pdf>
23. IRENA. (2019). *Innovation landscape brief: Artificial intelligence and big data*. Abu Dhabi: International Renewable Energy Agency. Retrieved from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Sep/IRENA_AI_Big_Data_2019.pdf
24. Kajda, K., & Karwot, J. (2025). The role of artificial intelligence in revolutionizing industrial automation for municipal waste management in Industry 4.0. *Green Transition and Sustainable Development*, 1(1), 37-63. [https://doi.org/10.61093/gtsd.1\(1\).37-63.2025](https://doi.org/10.61093/gtsd.1(1).37-63.2025)
25. Khan, M. R., Haider, Z. M., Malik, F. H., Almasoudi, F. M., Alatawi, K. S. S., & Bhutta, M. S. (2024). A comprehensive review of microgrid energy management strategies considering electric vehicles, energy storage systems, and AI techniques. *Processes*, 12(2), Article 270. <https://doi.org/10.3390/pr12020270>
26. Kildei, A., Tumpach, M., & Shafranova, K. (2025). Artificial intelligence for smart customer feedback management: Improving content analysis approaches. *Knowledge Economy and Lifelong Learning*, 1(1), 48-65. [https://doi.org/10.61093/kell.1\(1\).48-65.2025](https://doi.org/10.61093/kell.1(1).48-65.2025)
27. Koldov'skyi, A., Babenko, K., Shafranova, K., & Dyvyn'ska, Y. (2025). The role of AI in enhancing sustainable business leadership and organizational resilience. *Business Ethics and Leadership*, 9(2), 188-199. [https://doi.org/10.61093/bel.9\(2\).188-199.2025](https://doi.org/10.61093/bel.9(2).188-199.2025)
28. Kontautienė, R., Stravinskas, T., & Barkauskas, V. (2024). Forecasts of sustainable consumption in small economies. *Journal of International Studies*, 17(2), 9-37. <https://doi.org/10.14254/2071-8330.2024/17-2/1>
29. Kozhakhmetova, A., Mamyrbayev, A., Zhidebekkyzy, A., & Bilan, S. (2024). Assessing the impact of artificial intelligence on project efficiency enhancement. *Knowledge and Performance Management*, 8(2), 109-126. [https://doi.org/10.21511/kpm.08\(2\).2024.09](https://doi.org/10.21511/kpm.08(2).2024.09)
30. Kritikos, I., Sarantopoulos, A., Roumeliotis, A., Vasiliades, J., &

- Matsinas, I. (2025). Unlocking the potential of artificial intelligence in pharma research and development: Insights from investor and researcher perspectives. *Health Economics and Management Review*, 6(2), 1-16. <https://doi.org/10.61093/hem.2025.2-01>
31. Kumar, S.D.K., & Kumar J.P.S. (2024). Efficiency assessment and trends in the insurance industry: A bibliometric analysis of DEA application. *Insurance Markets and Companies*, 15(1), 83-98. [https://doi.org/10.21511/ins.15\(1\).2024.07](https://doi.org/10.21511/ins.15(1).2024.07)
 32. Kurbatova, T., Sotnyk, I., Prokopenko, O., Bashynska, I., & Pysmenna, U. (2023). Improving the feed-in tariff policy for renewable energy promotion in Ukraine's households. *Energies*, 16(19), Article 6773. <https://doi.org/10.3390/en16196773>
 33. Kuzior, A., Kovalenko, Y., Tiutiunyk, I., & Hrytsenko, L. (2025). Assessment of the energy security of EU countries in light of the expansion of renewable energy sources. *Energies*, 18(8), Article 2126. <https://doi.org/10.3390/en18082126>
 34. Kuzior, A., Sira, M., & Brozek, P. (2022). Using blockchain and artificial intelligence in energy management as a tool to achieve energy efficiency. *Virtual Economics*, 5(3), 69-90. [https://doi.org/10.34021/ve.2022.05.03\(4\)](https://doi.org/10.34021/ve.2022.05.03(4))
 35. Lazaroiu, G., & Rogalska, E. (2024). Generative artificial intelligence marketing, algorithmic predictive modelling, and customer behaviour analytics in the multisensory, extended reality metaverse. *Oeconomia Copernicana*, 15(3), 825-835. <https://doi.org/10.24136/oc.3190>
 36. Li, R., Xin, Y., Sotnyk, I., Kubatko, O., Almashaqbeh, I., Fedyna, S., & Prokopenko, O. (2022). Energy poverty and energy efficiency in emerging economies. *International Journal of Environment and Pollution*, 69(1-2), 1-21. <https://doi.org/10.1504/IJEP.2021.125188>
 37. Liu, Z., Zhang, X., Sun, Y., & Zhou, Y. (2023). Advanced controls on energy reliability, flexibility, resilience, and occupant-centric control for smart and energy-efficient buildings – A state-of-the-art review. *Energy and Buildings*, 297, Article 113436. <https://doi.org/10.1016/j.enbuild.2023.113436>
 38. Lyeonov, S., Podosynnikov, S., & Strielkowski, W. (2025a). Does a reliable electricity grid connection matter for the development of European renewable energy start-ups? *Energy Policy*, 206, Article 114749. <https://doi.org/10.1016/j.enpol.2025.114749>
 39. Lyeonov, S., Rosokhata, A., Bilan, S., Khomenko, L., Kuznyetsova, A., Myroshnychenko, I., & Letunovska, N. (2025b). Emotion-based insights into pro-environmental video campaigns: A study on waste sorting behavior in Ukraine. *Environmental Economics*, 16(2), 50-72. [https://doi.org/10.21511/ee.16\(2\).2025.05](https://doi.org/10.21511/ee.16(2).2025.05)
 40. Lyeonov, S., Serhiienko, R., Kašáková, E., Bato, V., Luptáková, A., Avetikyan, V., & Avetikyan, A. (2025c). Public interest and scholarly output on renewable energy and the shadow economy: Evidence from Google Trends and academic databases. *Knowledge and Performance Management*, 9(2), 95-112. [https://doi.org/10.21511/kpm.09\(2\).2025.08](https://doi.org/10.21511/kpm.09(2).2025.08)
 41. Mukhtarov, S., Aliyev, J., Jabiyev, F., & Aslan, D. H. (2024). The role of institutional quality in reducing environmental degradation in Canada. *Economics and Sociology*, 17(1), 89-102. <https://doi.org/10.14254/2071-789X.2024/17-1/6>
 42. Mura, L., & Stehlíková, B. (2025). The ethics of artificial intelligence: Safeguarding human dignity, social justice and environmental stability in the age of AI. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 20(2), 479-507. <https://doi.org/10.24136/eq.3743>
 43. Oesterreich, M., & Barej-Kaczmarek, E. (2024). Assessment of energy poverty in EU countries in 2010–2022. *Journal of International Studies*, 17(2), 75-99. <https://doi.org/10.14254/2071-8330.2024/17-2/4>
 44. Piwowarski, B. (2024). Increasing energy awareness through effective advertising messages – A neurophysiological approach to engagement study. *Human Technology*, 20(3), 676-700. <https://doi.org/10.14254/1795-6889.2024.20-3.12>
 45. Pollifroni, M., Ioana, A., Canuta, I. L., & Pollifroni, F. (2025). AI-driven e-recruitment in education and science: Moving towards good governance, prevention of corruption, administrative transparency, and bias-free decision-making. *Business Ethics and Leadership*, 9(2), 225-237. [https://doi.org/10.61093/bel.9\(2\).225-237.2025](https://doi.org/10.61093/bel.9(2).225-237.2025)
 46. Prokopenko, O., Kurbatova, T., Khalilova, M., Zerkal, A., Prause, G., Binda, J., Berdiyrov, T., Klapkiv, Y., Sanetra-Pólgrabi, S., & Komarnitskyi, I. (2023). Impact of investments and R&D costs in renewable energy technologies on companies' profitability indicators: Assessment and forecast. *Energies*, 16(3), Article 1021. <https://doi.org/10.3390/en16031021>
 47. Samusevych, Y., Račca, I., Vasylieva, T., & Tóth, A. (2024). Environmental tax reform efficiency: Prerequisites and consequences. *Journal of International Studies*, 17(4), 90-108. <https://doi.org/10.14254/2071-8330.2024/17-4/6>
 48. Sidii, F. S. (2024). Navigating the intersection of digital security, resilience and sustainability in healthcare: A theoretical framework and case study of Ghana. *Health Economics and Management Review*, 5(4), 130-146. <https://doi.org/10.61093/hem.2024.4-09>
 49. Sitnicki, M. W., Horbas, I., Derkach, O., Flowers, A., Wielewska, I., Tucki, K., Zuzek, D. K., & Pimenov, S. (2024a). Development and support of Ukrainian domestic entrepreneurship in the knowledge economy. *Sustainability*, 16(13), Article 5682. <https://doi.org/10.3390/su16135682>
 50. Sitnicki, M. W., Prykaziuk, N., Ludmila, H., Pimenowa, O., Imbrea, F., Şmuleac, L., & Paşcalău,

- R. (2024b). Regional perspective of using cyber insurance as a tool for protection of Agriculture 4.0. *Agriculture*, 14(2), Article 320. <https://doi.org/10.3390/agriculture14020320>
51. Stanford University. (n.d.). *Global AI vibrancy tool – AI index*. Stanford University Human-Centered Artificial Intelligence. Retrieved from <https://aiindex.stanford.edu/vibrancy>
 52. United Nations Statistics Division Development Data and Outreach Branch (UNSD). (2024). *SDG Indicators. Goal 7: Affordable and clean energy*. UNSD. Retrieved from <https://unstats.un.org/sdgs/report/2024/Goal-07/>
 53. Vakulenko, I., & Rekunenko, I. (2025). *Clean energy projects for European integration and cooperation* (185 p.). Hamburg, Germany: The Academic Research and Publishing UG (i. G.). <https://doi.org/10.61093/978-3-911748-03-2/2025>
 54. Wang, X., Wang, K., Safi, A., & Umar, M. (2025). How is artificial intelligence technology transforming energy security? New evidence from global supply chains. *Oeconomia Copernicana*, 16(1), 15-38. <https://doi.org/10.24136/oc.3488>
 55. Waqas, U., Umair, S., Mrugal-ska, B., & Ali Sulaiman, M. A. B. (2025). Twin transformation: The role of digitalization with artificial intelligence, big data and circular supply chain in circular economy performance for sustainability. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 20(2), 613-645. <https://doi.org/10.24136/eq.3350>
 56. Wiczorek, A., & Postrzednik-Lotko, K. (2025). Machine learning algorithms on social media: Privacy risks, user awareness and security implications. *Safety and Security Advances*, 1(1), 18-43. [https://doi.org/10.61093/ssa.1\(1\).18-43.2025](https://doi.org/10.61093/ssa.1(1).18-43.2025)
 57. World Bank. (2025, June 23). *Energy: Affordable, accessible energy is at the heart of development, driving job creation, growth, and shared prosperity*. Retrieved from <https://www.worldbank.org/en/topic/energy/overview>
 58. World Bank. (n.d.). *World Bank Open Data*. Retrieved from <https://data.worldbank.org/indicator>
 59. World Energy Council. (n.d.). *WEC Energy Trilemma Index Tool*. WEC Energy Trilemma Index Tool. Retrieved from <https://trilemma.worldenergy.org/>
 60. Yarovenko, H., Horbachova, O., Bylbas, R., & Latysh, D. (2025). Digitalization as a socio-economic challenge: Modeling the impact on the level of cybercrime considering socio-economic, technological and institutional factors. *SocioEconomic Challenges*, 9(2), 282-315. [https://doi.org/10.61093/sec.9\(2\).282-315.2025](https://doi.org/10.61093/sec.9(2).282-315.2025)
 61. Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024). The future of artificial intelligence: Fear, hope or indifference? *Human Technology*, 20(3), 611-639. <https://doi.org/10.14254/1795-6889.2024.20-3.10>
 62. Zakharchenko, A., Kushnerov, O., Kubaščíkova, Z., & Babenko, K. (2025). An intelligent system for predicting staff turnover in HR processes based on neural networks. *Knowledge Economy and Lifelong Learning*, 1(1), 35-47. [https://doi.org/10.61093/kell.1\(1\).35-47.2025](https://doi.org/10.61093/kell.1(1).35-47.2025)
 63. Zaryczańska, K., & Karwot, J. (2025). Analysis of occupational safety and health at the construction site based on images acquired from various sources using artificial intelligence. *Safety and Security Advances*, 1(1), 1-17. [https://doi.org/10.61093/ssa.1\(1\).1-17.2025](https://doi.org/10.61093/ssa.1(1).1-17.2025)