

Artificial Intelligence, Institutional Quality, and Electricity Network Efficiency: Evidence from the Global Energy Transition

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ARTICLE INFO			ABSTRACT
Article History:			Despite growing recognition of artificial intelligence (AI) as a general-purpose technology, limited attention has been paid to its role in improving electricity network efficiency and the institutional conditions under which these effects emerge. This study examines how AI development influences electricity network efficiency, proxied inversely by electricity transmission and distribution losses, and whether institutional quality strengthens this relationship within the global energy transition. Using panel data for 59 countries over 2010-2024, the analysis employs two-way fixed effects, instrumental variable generalized method of moments (IV-GMM), and method-of-moments quantile regression (MM-QR) to address endogeneity and capture distributional heterogeneity. The results show that AI development significantly improves electricity network efficiency by reducing transmission and distribution losses, with stronger effects observed in high-loss environments. Institutional quality further amplifies these efficiency gains, indicating that governance capacity and digital capability operate as complementary inputs. Heterogeneity analysis shows that the efficiency-enhancing effect of AI is more pronounced in fossil-fuel-dominant systems and technologically advanced economies. The findings highlight that technological adoption alone is insufficient; governance alignment is essential for translating digital capability into operational performance gains. This study contributes to the literature by providing cross-country evidence on the joint role of artificial intelligence and institutions in shaping electricity network efficiency and advancing the global energy transition.
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Introduction

The accelerating global transition toward decarbonization and electrification has elevated electricity-system efficiency to a central economic and environmental priority. Electricity currently accounts for nearly 20% of global final energy consumption and is projected to exceed 30% by 2040 as transport, heating, and industrial production become increasingly electrified (Agency, 2023). Global renewable capacity additions reached approximately 510 GW in 2023, representing a 50% increase compared with 2022 and the fastest annual expansion in two decades, reflecting the scale of electricity-based substitution required under the Paris Agreement (IEA, 2024; Rimšaitė, 2024; UNFCCC, 2022). However, the effectiveness of this expansion is critically conditioned by the performance of transmission and distribution (T&D) networks. Global average electricity losses remain close to 8% of total output (Bank, 2024), equivalent to more than 2,000 TWh annually. Cross-country disparities are substantial: loss rates are typically below 6% in advanced economies but exceed 15% in many developing countries and surpass 25% in several low-capacity systems (Niste et al., 2025). Figure 1 shows the negative association between artificial intelligence development and electricity transmission and distribution losses across countries, highlighting substantial heterogeneity in electricity system performance. Such inefficiencies increase generation requirements, intensify fiscal pressures, and dilute carbon-mitigation gains, positioning **electricity network inefficiency (proxied by electricity losses)** as a structural constraint on energy transition performance and infrastructure governance.

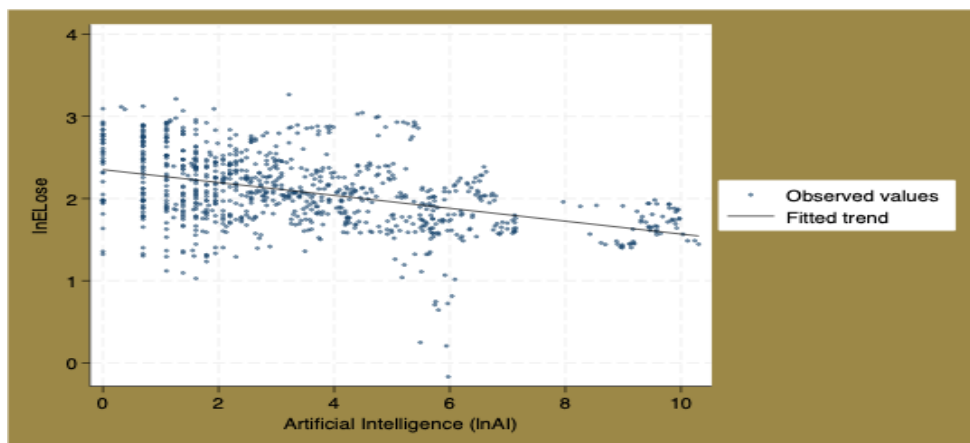


Figure 1. Relationship between artificial intelligence and electricity transmission and distribution losses.

Artificial intelligence (AI) is widely promoted as a transformative digital technology capable of addressing such inefficiencies (Zong & Guan, 2025). As a general-purpose technology embedded in smart grid architectures, AI enhances demand forecasting accuracy, enables predictive maintenance, facilitates anomaly detection, and optimizes real-time dispatch decisions (Azodo et al., 2025). Empirical evidence increasingly documents measurable operational improvements associated with AI deployment in energy systems. A recent systematic review of AI-enabled digital solutions in power systems reports that AI-driven predictive maintenance and digital-twin applications are associated with a 35% reduction in unplanned downtime, an 8.5% increase in energy production efficiency, 98.3% fault-detection accuracy, and a 26.2% reduction in operational energy costs (Abdessadak et al., 2025). These quantified performance gains suggest that computational intelligence can significantly enhance infrastructure efficiency. From this technology-optimistic perspective, AI appears well positioned to mitigate both technical losses

arising from congestion and equipment deterioration and non-technical losses associated with monitoring failures and irregular consumption.

However, the efficiency implications of AI in infrastructure systems remain theoretically unsettled. The expansion of digital infrastructure and data centers required to support AI applications increases electricity demand. Recent projections indicate that electricity consumption from data centers may increase by 40-148 TWh annually due to rapid digitalization and AI diffusion (IEA, 2024). Such expansion raises concerns regarding potential rebound effects that could partially offset technological efficiency gains. Moreover, the environmental and energy impacts of AI are found to be heterogeneous across institutional contexts. Cross-country evidence shows that AI-driven energy transition effects are significantly stronger in economies characterized by higher governance quality and institutional capacity (Q. Wang, F. Zhang, et al., 2024). These contrasting findings reveal a fundamental tension: does artificial intelligence inherently reduce infrastructure inefficiencies once adopted, or are its performance effects conditional upon institutional environments?

Existing literature on artificial intelligence and sustainable energy outcomes does not fully resolve this question. Empirical studies demonstrate that AI contributes to renewable energy integration, enhances energy efficiency, and supports carbon mitigation objectives (Q. Wang, Y. Li, et al., 2024; Wang, 2025). Firm-level analyses further show that AI adoption improves resource allocation and energy performance in industrial sectors (Li et al., 2023; Liu et al., 2022). Yet these analyses predominantly rely on aggregate indicators such as carbon emissions, renewable energy shares, or composite energy transition indices that obscure operational dynamics within electricity networks. Electricity network efficiency, commonly proxied through transmission and distribution losses, represents an indicator of grid-level performance, capturing both technical inefficiencies and governance-related distortions. Despite their structural importance, the relationship between AI development and electricity losses remains underexplored. Moreover, prior studies rarely integrate technological and institutional perspectives within a unified framework capable of explaining how digital capability translates into operational efficiency across heterogeneous governance environments.

This gap reflects a broader conceptual blind spot in the literature. Digital transformation research often assumes that technological capability translates into productivity or efficiency gains once adopted, while institutional economics emphasizes governance quality without explicitly incorporating digital technological capacity. The interaction between artificial intelligence and institutional quality in shaping infrastructure performance remains theoretically underdeveloped. If digital technologies require supportive governance structures to generate measurable efficiency gains, then AI's impact on electricity losses should vary systematically across institutional environments. Against this backdrop, this study examines whether artificial intelligence development improves electricity network efficiency, proxied inversely by electricity transmission and distribution losses, and whether institutional quality conditions this relationship. Specifically, we address the following research questions:

1. Does artificial intelligence development significantly improve electricity network efficiency by reducing transmission and distribution losses?
2. Does institutional quality moderate the relationship between artificial intelligence and electricity network efficiency?
3. Under which institutional environments can digital transformation most effectively enhance grid efficiency and support sustainable power-sector development?

First, this study advances a technology-institution complementarity perspective on infrastructure efficiency. Rather than assuming that artificial intelligence automatically improves operational performance, we conceptualize electricity transmission and distribution losses as an outcome of alignment between digital technological capability and institutional governance capacity. By reframing grid inefficiency through this conditional lens, the study moves beyond a linear “technology improves efficiency” narrative and demonstrates that digital transformation in infrastructure systems operates through institutionalized translation mechanisms.

Second, the paper extends the digital transformation and sustainable energy literature by introducing electricity network efficiency, operationalized through transmission and distribution losses, as a theoretically meaningful performance indicator. Prior research predominantly focuses on aggregate outcomes such as carbon emissions, renewable energy shares, or energy transition indices, which often obscure operational inefficiencies within electricity networks. By identifying a grid-efficiency channel, this study clarifies how artificial intelligence affects the micro-foundations of power-system performance, thereby deepening theoretical understanding of digital infrastructure optimization.

Third, the study provides systematic cross-country evidence on the conditional effectiveness of artificial intelligence in improving electricity network efficiency. Using a multi-country panel framework and distribution-sensitive estimators, the analysis demonstrates that the loss-reducing impact of AI varies across institutional environments, technological maturity levels, and electricity structure types. This heterogeneity analysis strengthens the external validity of the complementarity argument and highlights that digital efficiency gains are structurally contingent rather than universally uniform.

Fourth, the findings contribute to policy and governance debates by demonstrating that technological adoption alone is insufficient to achieve infrastructural efficiency gains. The results indicate that institutional reforms, particularly improvements in regulatory quality, enforcement credibility, and administrative coordination are necessary to unlock the operational benefits of artificial intelligence in electricity systems. By emphasizing alignment between digital capability and governance structures, the study offers a more nuanced framework for designing digitalization strategies that support long-term energy transition objectives.

2. Literature Review

2.1 Determinants of Electricity Network Efficiency

Electricity network efficiency, commonly proxied through electricity transmission and distribution (T&D) losses, is widely recognized as a critical dimension of power-system performance. Existing literature identifies several determinants of electricity losses, which can be broadly categorized into technical, economic, and institutional factors (Mukherjee et al., 2023; Niste et al., 2025). From a technical perspective, infrastructure quality plays a decisive role. Aging transmission lines, insufficient grid interconnection, high network resistance, and inadequate maintenance increase technical losses, particularly in countries with limited capital investment in grid modernization (Ertugrul, 2024; Kabeyi & Olanrewaju, 2023). Rapid electrification and demand growth can further strain grid capacity, generating congestion and overload conditions that elevate energy dissipation.

Economic and structural characteristics also influence T&D losses. Industrial composition affects load profiles and network utilization efficiency, as energy-intensive industries and uneven regional demand distribution complicate grid management (Jiang et al., 2025; Xing & Jia, 2024).

Urbanization, population density, and demand volatility can increase operational complexity, requiring more sophisticated dispatch and balancing mechanisms (Fatorachian, 2025). Fiscal constraints and limited public investment capacity may hinder infrastructure upgrading, especially in developing economies, thereby perpetuating inefficiencies (Yohou, 2023).

Institutional and governance factors are particularly important in explaining non-technical losses. Weak regulatory enforcement, corruption, electricity theft, and billing inefficiencies significantly increase aggregate losses in many emerging markets (Kumar et al., 2025). Insufficient monitoring systems and limited administrative capacity reduce the ability to detect illegal connections and unauthorized consumption. Empirical evidence consistently shows that stronger governance structures, improved regulatory quality, and higher transparency levels are associated with lower non-technical losses (McCormack et al., 2025; Nel & Taeihagh, 2025). Therefore, this literature underscores that electricity network efficiency, as reflected in T&D losses, is shaped not only by engineering constraints but also by deeper institutional and structural conditions.

2.2 Artificial Intelligence and Power-System Efficiency

A growing body of research examines the role of artificial intelligence and digital technologies in improving energy-system performance. As a general-purpose technology, artificial intelligence enables real-time data processing, predictive analytics, and automated decision-making, which are increasingly embedded in smart grid architectures (Rajaperumal & Columbus, 2025). AI-driven demand forecasting improves load prediction accuracy, reduces balancing errors, and enhances dispatch efficiency (X. Wang et al., 2024). Predictive maintenance systems identify equipment vulnerabilities before failure occurs, thereby minimizing downtime and reducing technical losses (Sinnah, 2025). In addition, anomaly detection algorithms can assist utilities in identifying irregular consumption patterns and potential electricity theft, directly addressing non-technical losses (Zeb & Lodhi, 2025).

Beyond grid operations, empirical studies highlight AI's broader contribution to energy transition processes. Artificial intelligence has been found to enhance energy efficiency, support renewable energy integration, and facilitate low-carbon transformation through digital optimization and technological innovation (Chen et al., 2021). By improving resource allocation and operational coordination, AI may lower energy intensity and strengthen environmental performance (Shaik et al., 2024). However, the impact of AI development on energy outcomes is not uniformly positive. The expansion of digital infrastructure, data centers, and computational systems may increase electricity demand, potentially generating rebound effects that offset efficiency gains. Moreover, the effectiveness of AI adoption may vary across countries depending on technological readiness, economic structure, and regulatory conditions. These findings suggest that while AI possesses substantial potential to enhance power-system efficiency, its aggregate influence on operational inefficiencies such as electricity transmission and distribution losses remains theoretically underdeveloped and empirically underexplored.

2.3 Institutional Quality, Digital Transformation, and Energy Outcomes

Institutional quality has long been recognized as a fundamental determinant of economic and energy-sector performance. Strong institutions improve regulatory enforcement, enhance transparency, and strengthen public-sector accountability, thereby facilitating efficient infrastructure investment and energy management (Song et al., 2024). In the electricity sector, governance quality influences tariff implementation, billing systems, anti-theft enforcement, and maintenance oversight, all of which directly affect T&D losses (Kumar et al., 2025). Recent research further suggests that the effectiveness of technological innovation may depend on

complementary institutional conditions. Digital transformation initiatives require coordination capacity, regulatory clarity, and credible enforcement mechanisms to translate technological potential into measurable efficiency gains (Wang et al., 2025). In weak institutional environments, the deployment of advanced monitoring technologies may not yield expected improvements due to limited administrative capacity or governance constraints (Khan, 2022). Accordingly, institutional quality may condition the relationship between artificial intelligence development and electricity system performance. This suggests that the effect of AI may depend not only on technological capability itself, but on complementarity between digital innovation and institutional governance.

2.4 Research Gap

Existing research identifies infrastructure quality, economic structure, and governance conditions as key determinants of electricity transmission and distribution losses, while a separate literature emphasizes artificial intelligence as a driver of energy efficiency and low-carbon transition. However, these strands have largely developed independently. Studies on electricity network efficiency rarely incorporate digital technological advancement as a central explanatory factor, while research on AI and energy outcomes typically overlooks grid-level operational efficiency, often proxied through T&D losses. Moreover, although institutional quality is recognized as critical for energy-sector performance, its role in conditioning the effectiveness of AI deployment remains insufficiently examined. An integrated framework linking AI, institutional quality, and electricity network efficiency, operationalized through T&D losses, is therefore needed.

3. Theory and Conceptual Framework

3.1 Technology-Institution Complementarity in Electricity Network Efficiency

Electricity transmission and distribution (T&D) losses reflect systemic inefficiencies arising from both technical constraints and governance frictions within power systems. Technical losses originate from network resistance, congestion, equipment deterioration, and imperfect load balancing, while non-technical losses stem from weak monitoring systems, electricity theft, billing inefficiencies, and regulatory enforcement failures (Ghadi et al., 2025). As electricity systems become increasingly complex due to electrification, decentralization, and renewable integration, reducing T&D losses requires more than physical infrastructure expansion; it demands enhanced coordination, information processing capacity, and institutional alignment (Gallegos et al., 2024).

From the perspective of Technological Innovation Systems (TIS), artificial intelligence (AI) represents a general-purpose digital technology that enhances system-level information processing, predictive capability, and adaptive coordination (Ilcic et al., 2025). AI-driven forecasting, predictive maintenance, anomaly detection, and real-time dispatch optimization can improve demand-supply synchronization and reduce congestion-induced inefficiencies. Within complex infrastructure networks characterized by interdependence and volatility, such computational intelligence has the potential to reduce operational friction and enhance efficiency (Adetula & Akanbi, 2023). However, TIS primarily explains technological capability formation and diffusion; it does not fully specify the institutional conditions required to translate digital capability into measurable performance outcomes. Institutional economics, in contrast, emphasizes the role of governance quality, regulatory enforcement, and administrative capacity in reducing coordination failures and transaction costs (Greif, 2025). Strong institutions enhance transparency, ensure compliance, and facilitate effective policy implementation, thereby shaping infrastructure performance (Usman et al., 2024). Yet institutional theory often treats technological inputs as exogenous, leaving the interaction between digital capability and governance quality theoretically underdeveloped (Schiavi et al., 2024).

This study integrates these perspectives by proposing a Technology-Institution Complementarity Framework, in which infrastructure efficiency emerges from the alignment between AI-driven optimization capacity and institutional governance strength. Under this framework, digital technological capability and institutional quality function as complementary inputs. Artificial intelligence enhances operational coordination, but its efficiency effects are amplified or constrained by the surrounding governance environment. An alternative technology-dominant perspective would predict that AI, as a general-purpose technology, reduces inefficiencies independently of institutional conditions once adopted. According to this view, computational optimization operates autonomously and should generate uniform efficiency gains across contexts. However, this assumption overlooks implementation frictions, regulatory inconsistencies, and enforcement weaknesses that may prevent digital tools from translating into operational improvements. The complementarity framework advanced here challenges this automatic-efficiency assumption by arguing that technological capability alone is insufficient without institutional alignment.

3.2 Artificial Intelligence and Electricity Transmission and Distribution Losses

Within the Technology-Institution Complementarity Framework, artificial intelligence reduces electricity T&D losses through a structural optimization channel. Electricity networks operate under conditions of high interdependence, demand volatility, and real-time balancing constraints (Rosales-Asensio et al., 2024). AI improves load forecasting accuracy, enables predictive maintenance of transmission infrastructure, facilitates anomaly detection in consumption patterns, and optimizes dispatch decisions (X. Wang et al., 2024). These mechanisms reduce congestion-related dissipation, minimize equipment failures, and enhance synchronization between electricity supply and demand. By embedding computational intelligence into grid management systems, AI strengthens dynamic adjustment capacity and reduces operational inefficiencies across both technical and non-technical dimensions. Improved monitoring and data analytics can also increase transparency within electricity networks, lowering the incidence of electricity theft and billing irregularities. Consequently, as AI development deepens and digital capabilities expand, electricity systems are expected to exhibit improved coordination efficiency and lower aggregate losses. Accordingly, the complementarity framework predicts a baseline efficiency effect of artificial intelligence:

H1: AI improves electricity network efficiency by reducing electricity transmission and distribution losses.

3.3 Moderating Role of Institutional Quality

While AI provides the technological means to enhance grid efficiency, the realization of these gains depends critically on institutional conditions. Institutional quality shapes the credibility of regulatory enforcement, the transparency of governance mechanisms, and the effectiveness of administrative coordination (Zaman et al., 2026). In institutional environments characterized by strong rule of law, regulatory stability, and low corruption, digital infrastructure investments are more likely to be effectively implemented, integrated, and maintained (De Pascale et al., 2024). Clear regulatory frameworks facilitate data interoperability, strengthen compliance, and enhance anti-theft enforcement, thereby magnifying the operational benefits of AI-enabled systems. On the other hand, in weak institutional environments, governance inefficiencies, inconsistent regulation, and limited enforcement capacity may constrain the translation of digital capability into performance improvements. AI adoption may occur without effective utilization, monitoring systems may lack enforcement support, and technological investments may fail to address entrenched non-technical losses (O. Shonubi, 2025; O. A. Shonubi, 2025). Under such conditions,

the efficiency impact of AI is attenuated. Within the Technology-Institution Complementarity Framework, institutional quality therefore conditions the magnitude of AI's efficiency effect. Digital capability and governance capacity jointly determine infrastructure performance. The loss-reducing effect of artificial intelligence is expected to be stronger where institutional quality is higher. Accordingly:

H2: Institutional quality positively moderates the relationship between AI development and electricity network efficiency, such that the loss-reducing effect of AI is stronger in countries with higher institutional quality.

Therefore, the preceding arguments establish both the direct effect of artificial intelligence development on electricity transmission and distribution losses (H1) and the conditional role of institutional quality in shaping this relationship (H2). Figure 2 summarizes the conceptual framework and illustrates the hypothesized relationships examined in the empirical analysis.

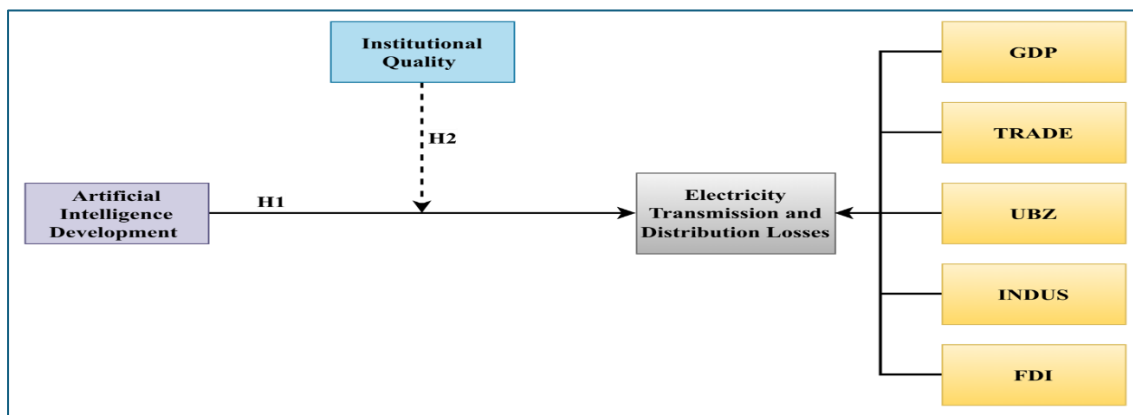


Figure: 2 Conceptual Framework and Hypothesized Relationships.

4. Data and Methodology

4.1 Econometric Specification

To examine the relationship between AI development and electricity T&D losses, we estimate the following two-way fixed-effects panel model:

$$ELoss_{it} = \alpha + \beta_1 AI_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Loss_{it}$ denotes electricity transmission and distribution losses in country i and year t ; AI_{it} represents the level of artificial intelligence development; and $\gamma' X_{it}$ is a vector of control variables capturing structural and macroeconomic determinants of electricity losses. Country fixed effects (μ_i) account for time-invariant heterogeneity such as geography, historical infrastructure conditions, and baseline institutional characteristics, while year fixed effects (λ_t) control for global shocks affecting electricity systems and technological diffusion. To assess the moderating role of institutional quality, we augment the baseline model with an interaction term:

$$ELoss_{it} = \alpha + \beta_1 AI_{it} + \beta_2 lnIQ_{it} + \beta_3 (AI_{it} \times lnIQ_{it}) + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where $lnIQ_{it}$ captures institutional quality. A statistically significant interaction coefficient (β_3) indicates that institutional conditions condition the effectiveness of AI in reducing electricity losses.

4.2 Variable Definition and Measurement

Dependent Variable

Electricity network efficiency is proxied inversely by electricity transmission and distribution losses, measured as the percentage of electricity output lost during transmission and distribution relative to total electricity production (World Bank, indicator EG.ELC.LOSS.ZS). This indicator captures both technical inefficiencies such as network resistance, equipment losses and non-technical losses such as theft, billing irregularities, and serves as a direct proxy for grid-level operational performance. The variable is log-transformed (lnELose) to reduce skewness and facilitate elasticity interpretation.

Independent Variable

Artificial intelligence (AI) development is proxied by the total number of AI-related patent applications obtained from the World Intellectual Property Organization (WIPO) PATENTSCOPE database. AI patents are identified using IPC classifications corresponding to artificial intelligence technologies. Patent counts capture innovative output and national technological capability in digital intelligence domains. The variable is log-transformed (lnAI) to mitigate skewness and reduce scale effects across countries.

Moderating Variable

Institutional quality is measured using the Worldwide Governance Indicators (WGI) from the World Bank. We construct a composite index based on rule of law, regulatory quality, and government effectiveness. These dimensions capture enforcement credibility, administrative capacity, and regulatory stability. Higher values indicate stronger governance environments and greater institutional capacity to support effective policy implementation.

Control Variables

Consistent with the electricity loss literature, the model includes controls for: Economic development (GDP per capita), trade, Urbanization rate, Industrial structure (industry value-added share), and foreign direct investment. These variables account for demand structure, infrastructure burden, and structural transformation that may independently affect electricity losses. These variables are detailed in Table 1.

Table 1. Data Sources and Variable Construction

Variable	Definition	Measurement	Data Source
lnELose	Electricity transmission and distribution losses	Electric power transmission and distribution losses (% of output)	World Bank, 2025
lnAI	Artificial intelligence development intensity	Total AI-related patent applications	World Intellectual Property Organization database, 2025
lnGDP	Level of economic development	GDP per capita (constant 2015 US\$)	World Bank, 2025
lnTRADE	Trade integration level	Trade (% of GDP)	World Bank, 2025
lnUBZ	Urban development level	Urban population (% of total population)	World Bank, 2025

lnINDUS	Industrialization level	Industry value added (% of GDP)	World Bank, 2025
lnFDI	External capital inflows	FDI net inflows (% of GDP)	World Bank, 2025
IQ	Governance and regulatory capacity	Composite index of Worldwide Governance Indicators (rule of law, regulatory quality, government effectiveness)	World Bank, 2025

Notes: All monetary variables are expressed in constant prices where applicable. Variables exhibiting skewness are logarithmically transformed to mitigate heteroskedasticity. Missing observations are addressed through standard data cleaning procedures. AI patent data are extracted from the World Intellectual Property Organization (WIPO) PATENTSCOPE database using IPC classifications related to artificial intelligence technologies.

4.3 Estimation Strategy and Identification Considerations

Given the cross-country nature of the dataset panel of 59 countries covering 2010-2024, unobserved heterogeneity, serial correlation, and cross-sectional dependence may bias conventional panel estimators. As shown in Figure 3 and Table 2, the data exhibit standard distributional properties and variability across countries. The inclusion of country and year fixed effects mitigates omitted variable bias arising from time-invariant heterogeneity and global shocks.

To ensure robust inference, standard errors are estimated using the Driscoll-Kraay procedure, which provides consistency in the presence of heteroskedasticity, autocorrelation, and cross-sectional dependence. This approach is particularly appropriate in macro-panel settings where global economic integration and technological diffusion generate correlated shocks across countries. Potential endogeneity concerns may arise from reverse causality and omitted variable bias. To address this issue, this study employs an instrumental variable generalized method of moments (IV-GMM) approach. Following standard practice in macro-panel studies, lagged values of artificial intelligence development are used as instruments, capturing the persistence of technological capability while reducing contemporaneous feedback effects from electricity system performance. Although this strategy mitigates endogeneity concerns, it may not fully eliminate all sources of bias; therefore, results are interpreted with appropriate caution. In addition, lagged independent variables and alternative model specifications are employed as robustness checks to further strengthen the credibility of the empirical findings.

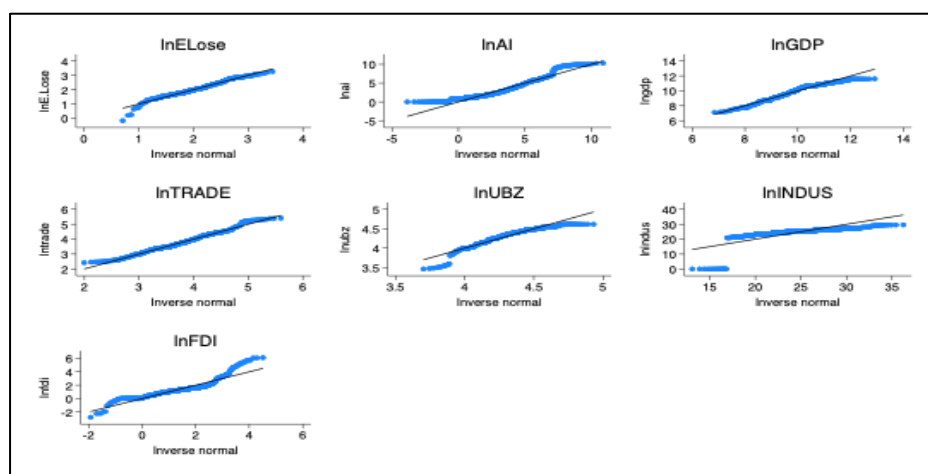


Figure 3: Reference line indicates theoretical normal distribution

Table 2. Descriptive Statistics of the Variables

Variable	Mean	Std. Dev.	Min	Median	Max
lnELose	2.0763	0.4487	-0.1675	2.0429	3.2659
lnAI	3.5137	2.4104	0.0000	2.9780	10.3062
lnGDP	9.8795	0.9936	7.1198	9.9911	11.6162
lnTRADE	3.7968	0.5902	2.4172	3.7541	5.4086
lnUBZ	4.3163	0.2015	3.4627	4.3593	4.6151
lnINDUS	24.6537	3.7911	0.0000	25.2445	29.5728
lnFDI	1.2940	1.0539	-2.7988	1.2127	6.1164

Notes: All variables are logarithmically transformed. The sample consists of 59 countries over the period 2010-2024 (N = 885).

5. Findings

5.1 Preliminary Analysis

Preliminary diagnostic tests are reported in Tables 3-6. The (Pesaran, 2004) CD statistics reveal significant cross-sectional dependence across all variables, necessitating the use of second-generation panel techniques. The CIPS unit root results (Pesaran, 2007) indicate that most variables are stationary at levels or after first differencing, suggesting mixed integration orders. The (Pesaran & Yamagata, 2008) slope heterogeneity tests reject the null of homogeneous slopes, supporting heterogeneous panel specifications. Additionally, the (Westerlund, 2007) cointegration test confirms the presence of a long-run equilibrium relationship among the variables, justifying the estimation of long-run panel models.

Table 3. Cross-Sectional Dependence (CSD)-Pesaran CD

Statistics	lnELose	lnAI	lnGDP	lnTRADE	lnUBZ	lnINDUS	lnFDI
CD Statistic	7.33	18.49	91.87	33.71	65.96	57.55	8.73
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: p-values are reported in parentheses; all are <0.001, shown as 0.000.

Table 4. Unit Root Test (CIPS, Pesaran 2007)

CIPS	lnELose	lnAI	lnGDP	lnTRADE	lnUBZ	lnINDUS	lnFDI
I(0)	-2.275**	-2.248**	-2.204**	-1.496	-2.105*	-1.429	-1.648
I(1)	-2.713***	-2.918***	-2.176**	-1.698	-1.346	-1.644	-2.939***

Notes: Reported values are the t-bar (CIPS) statistics from pescadf with constant and lags(1). Critical values: cv10 = -2.010, cv5 = -2.090, cv1 = -2.230. ***, **, * denote rejection of unit root at 1%, 5%, 10%.

Table 5. Slope Heterogeneity Test

Test	Statistic	p-value
Δ (Delta)	8.180***	0.000
Δ_{adj} (Adjusted Delta)	11.975***	0.000

Note: *** indicates statistical significance at the 1% level. H_0 : Slope coefficients are homogeneous across countries.

Table 6. Westerlund Cointegration Test

Statistic	Gt	Ga	Pt	Pa
Model	-6.664***	-0.369	-4.495	-0.468

Note: *** indicates statistical significance at the 1% level.

5.2 Baseline Regression Results

Table 7 reports the baseline regression results examining the relationship between artificial intelligence development and electricity transmission and distribution (T&D) losses across multiple estimators. Across all specifications, the coefficient on $\ln AI$ remains negative and statistically significant at the 1% level, indicating a robust loss-reducing effect of AI development. The magnitude varies across models, ranging from -0.030 in the fixed-effects (FE) model to -0.060 in the IV-GMM specification, suggesting that a 1% increase in AI development is associated with approximately 0.03%-0.06% reductions in electricity losses. The FE estimates, which control for time-invariant country heterogeneity, confirm the baseline hypothesis (H1). Random-effects (RE) and FGLS models yield consistent signs and comparable magnitudes, reinforcing the stability of the relationship. Importantly, the IV-GMM results, using lagged AI as an instrument, remain strongly significant and display a slightly larger coefficient in absolute terms. The Kleibergen-Paap LM statistic rejects the null of underidentification, while the KP Wald F statistic substantially exceeds conventional critical thresholds, indicating instrument relevance and strength. These findings alleviate concerns regarding reverse causality and omitted variable bias.

Among control variables, GDP exhibits a consistently negative and significant association with electricity losses, suggesting that higher income levels are associated with more efficient grid systems. Trade openness displays mixed effects across specifications, reflecting potential structural heterogeneity. Industrial structure and FDI appear statistically insignificant in most models, indicating limited direct influence on electricity losses once country effects are controlled. Therefore, the baseline results provide strong empirical support for the hypothesis that artificial intelligence development contributes to reducing electricity transmission and distribution losses across countries.

Table 7. AI and Electricity Network Efficiency

Variable	OLS	FE	RE	IV-GMM
$\ln AI$	-0.0588*** (-10.50)	-0.0302*** (-2.66)	-0.0305*** (-3.16)	-0.0605*** (-9.34)
$\ln GDP$	-0.1708*** (-9.79)	-0.4239*** (-6.85)	-0.3175*** (-7.84)	-0.1647*** (-9.23)
$\ln TRADE$	-0.2209*** (-9.36)	0.1270*** (2.71)	0.0346 (0.87)	-0.2219*** (-7.12)
$\ln UBZ$	-0.1249* (-1.78)	0.1525 (0.71)	0.0908 (0.56)	-0.1509* (-1.90)
$\ln INDUS$	-0.0011 (-0.36)	-0.0018 (-0.42)	-0.0030 (-0.74)	-0.0011 (-0.65)
$\ln FDI$	0.0070 (0.63)	0.0029 (0.42)	0.0025 (0.37)	0.0086 (0.59)
Constant	5.3649*** (20.75)	5.2703*** (6.18)	4.8666*** (7.95)	5.4254*** (18.82)
Observations	885	885	885	826
KP LM statistic	—	—	—	239.75

KP LM (P-value)	—	—	—	0.000
KP Wald F	—	—	—	11646.06

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 MMQR Results

To examine whether the impact of artificial intelligence varies across the distribution of electricity T&D losses, Table 8 reports the results of the Method-of-Moments Quantile Regression (MM-QR). This approach allows the effect of AI to differ across countries characterized by low- versus high-loss environments, thereby capturing distributional heterogeneity that cannot be observed in mean-based estimators. The coefficient on AI is consistently negative and statistically significant across all quantiles (Q10-Q90), confirming the robustness of the loss-reducing effect. Importantly, the magnitude of the coefficient increases in absolute terms toward the upper quantiles, from -0.0487 at Q10 to -0.0694 at Q90. This pattern suggests that AI development exerts a stronger mitigating effect in countries experiencing higher levels of electricity losses. In other words, digital intelligence appears particularly effective in improving grid efficiency where inefficiencies are more pronounced. The significant negative location parameter further supports the overall mean-reducing effect of AI, while the negative and significant scale parameter indicates that AI may also reduce dispersion in electricity losses across countries.

Regarding control variables, GDP remains negatively associated with electricity losses across all quantiles, indicating that higher-income economies tend to exhibit more efficient grid systems throughout the distribution. Trade openness shows a diminishing negative effect at higher quantiles, suggesting heterogeneous structural dynamics. Urbanization demonstrates significance primarily in lower and middle quantiles, while industrial structure and FDI display mixed and distribution-sensitive effects. Notably, FDI shifts from negative at lower quantiles to positive at upper quantiles, implying that foreign investment may have heterogeneous implications depending on baseline system efficiency. Therefore, the MM-QR results reveal substantial distributional heterogeneity and confirm that artificial intelligence plays a stronger role in reducing electricity losses in high-loss contexts. These findings reinforce the baseline evidence and highlight the importance of accounting for cross-country structural differences when evaluating the digital transformation-energy efficiency nexus.

Table 8. MMQR Results

Variables	Location	Scale	Q10	Q25	Q50	Q75	Q90
lnAI	-0.0588*** (0.0052)	-0.0069** (0.0031)	-0.0487*** (0.0070)	-0.0528*** (0.0060)	-0.0585*** (0.0052)	-0.0651*** (0.0059)	-0.0694*** (0.0069)
lnGDP	-0.1708*** (0.0178)	0.0037 (0.0105)	-0.1762*** (0.0240)	-0.1741*** (0.0203)	-0.1710*** (0.0179)	-0.1674*** (0.0200)	-0.1651*** (0.0237)
lnTRADE	-0.2209*** (0.0248)	0.0240* (0.0146)	-0.2563*** (0.0334)	-0.2420*** (0.0283)	-0.2220*** (0.0248)	-0.1990*** (0.0278)	-0.1840*** (0.0329)
lnUBZ	-0.1249* (0.0718)	0.0300 (0.0424)	-0.1691* (0.0966)	-0.1512* (0.0819)	-0.1262* (0.0719)	-0.0975 (0.0805)	-0.0788 (0.0953)
lnINDUS	-0.0011 (0.0019)	0.0017 (0.0011)	-0.0035 (0.0026)	-0.0025 (0.0022)	-0.0011 (0.0019)	0.0005 (0.0021)	0.0015 (0.0025)
lnFDI	0.0070 (0.0142)	0.0446*** (0.0084)	-0.0586*** (0.0192)	-0.0322** (0.0161)	0.0050 (0.0144)	0.0477*** (0.0159)	0.0754*** (0.0187)
Constant	5.3649*** (0.2515)	-0.0797 (0.1485)	5.4821*** (0.3384)	5.4348*** (0.2869)	5.3684*** (0.2519)	5.2922*** (0.2819)	5.2427*** (0.3338)
Obs.	885	885	885	885	885	885	885

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4 Moderation Analysis

Table 9 presents the direct impact of institutional quality (IQ) on electricity T&D losses across multiple estimators. The OLS, FGLS, and IV-GMM results indicate that lnIQ is negatively and significantly associated with electricity losses, suggesting that stronger governance environments contribute to improved grid efficiency. However, the fixed-effects (FE) and random-effects (RE) estimates yield statistically insignificant coefficients, implying that the direct institutional effect is primarily driven by cross-country variation rather than within-country temporal changes.

The IV-GMM results confirm the robustness of this relationship. The Kleibergen-Paap LM statistic rejects underidentification, and the KP Wald F statistic substantially exceeds conventional thresholds, indicating instrument relevance and strength. These findings suggest that institutional quality exerts a structural influence on electricity loss reduction, consistent with the view that stronger regulatory enforcement and governance capacity mitigate non-technical losses and enhance system oversight. Notably, the coefficient on lnAI remains negative and statistically significant across specifications, indicating that the loss-reducing effect of artificial intelligence persists even after controlling for institutional conditions.

Table 9. Direct impact of Institutional Quality on Electricity Losses (lnELose)

Variable	OLS	FE	RE	FGLS	IV-GMM
lnIQ	−0.1210*** (−4.36)	0.0103 (0.30)	−0.0019 (−0.06)	−0.1210*** (−4.38)	−0.1216*** (−3.75)
lnAI	−0.0561*** (−9.97)	−0.0221* (−1.92)	−0.0246** (−2.52)	−0.0561*** (−10.02)	−0.0576*** (−8.76)
lnGDP	−0.1059*** (−4.50)	−0.4311*** (−6.98)	−0.3253*** (−7.61)	−0.1059*** (−4.52)	−0.0993*** (−3.84)
lnTRADE	−0.2141*** (−9.04)	0.1233** (2.55)	0.0323 (0.80)	−0.2141*** (−9.08)	−0.2149*** (−6.88)
lnUBZ	−0.2170*** (−2.92)	0.2200 (1.02)	0.1399 (0.86)	−0.2170*** (−2.94)	−0.2446*** (−2.81)
lnINDUS	−0.0013 (−0.43)	−0.0018 (−0.43)	−0.0029 (−0.74)	−0.0013 (−0.43)	−0.0013 (−0.74)
lnFDI	0.0122 (1.08)	0.0025 (0.37)	0.0020 (0.30)	0.0122 (1.09)	0.0139 (0.96)
Constant	5.1383*** (19.59)	5.0374*** (5.91)	4.7206*** (7.69)	5.1383*** (19.68)	5.1977*** (17.72)
Observation	870	870	870	870	813
KP LM (statistic)					236.961
KP LM (p-value)					0.000
KP Wald F					11448.00

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 10 reports the interaction results examining whether institutional quality conditions the relationship between artificial intelligence and electricity transmission and distribution losses. Column (1) presents the baseline effect of AI, while Column (2) introduces institutional quality as an independent determinant. Column (3) incorporates the interaction term between AI and institutional quality using an IV-GMM framework.

The interaction coefficient ($\ln AI \times \ln IQ$) is negative and statistically significant at the 1% level (-0.0519), indicating that institutional quality strengthens the loss-reducing effect of artificial intelligence. This finding suggests that the impact of AI on electricity transmission and distribution losses is not uniform across countries but depends on the level of governance quality. More specifically, the marginal effect of artificial intelligence becomes increasingly negative as institutional quality improves. This implies that the effectiveness of AI increases non-linearly with institutional quality. In countries characterized by stronger regulatory enforcement, higher administrative capacity, and more effective governance structures, AI-driven technologies such as predictive maintenance, anomaly detection, and real-time monitoring can be more effectively implemented and enforced, leading to greater reductions in electricity losses. In contrast, in weak institutional environments, the effectiveness of AI is constrained by governance limitations, reducing its ability to translate technological capability into operational efficiency gains.

These results provide strong empirical support for the Technology-Institution Complementarity Framework, demonstrating that digital technological capability and institutional quality operate as complementary factors in determining infrastructure efficiency. While artificial intelligence independently contributes to reducing electricity losses, its effectiveness is significantly amplified when supported by strong institutional frameworks. The validity of the instrumental variable strategy is confirmed by the Kleibergen-Paap statistics, which reject the null of underidentification and indicate strong instrument relevance. Overall, the findings highlight that technological advancement alone is insufficient; institutional alignment is essential for maximizing the efficiency gains from artificial intelligence in electricity systems.

Table 10. Results of the Moderating Role of Institutional Quality

Variable	(1)	(2)	(3)
$\ln AI$	-0.0588*** (-10.50)		
$\ln IQ$		-0.1769*** (-4.63)	
$\ln AI \times \ln IQ$			-0.0519*** (-7.01)
$\ln GDP$	-0.1708*** (-9.79)	-0.0742*** (-2.68)	-0.1356*** (-5.02)
$\ln TRADE$	-0.2209*** (-9.36)	-0.2098*** (-6.73)	-0.1531*** (-4.93)
$\ln UBZ$	-0.1249* (-1.78)	-0.2717*** (-3.08)	-0.1329 (-1.55)
$\ln INDUS$	-0.0011 (-0.36)	-0.0015 (-0.86)	-0.0061*** (-2.75)
$\ln FDI$	0.0070 (0.63)	0.0147 (1.01)	0.0093 (0.64)
Constant	5.3649*** (20.75)	5.0755*** (17.11)	4.8170*** (17.26)
Observations	885	808	749
KP LM (statistic)	239.75	40.98	239.03
KP LM (P-value)	0.000	0.000	0.000
KP Wald F	11646.06	80.50	6830.19

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Column (3) instruments $\ln AI \times \ln IQ$ using $L2.\ln ai_ \ln iq$.

5.5 Robustness Checks

5.5.1 Driscoll-Kraay Standard Errors

To further address potential cross-sectional dependence and serial correlation both common in macro-panel datasets we re-estimate the baseline model using Driscoll-Kraay (DK) standard errors. This approach produces inference robust to heteroskedasticity, autocorrelation, and cross-sectional correlation. As shown in Table 11, the coefficient on AI remains negative and statistically significant when country fixed effects and control variables are included. The magnitude is comparable to the baseline FE estimates, indicating that the loss-reducing effect of AI persists after correcting for cross-sectional dependence. Additionally, lagged AI specifications (L1 and L2) are introduced to mitigate potential reverse causality. The first lag remains statistically significant, while the second lag becomes insignificant, suggesting that the effect of AI on electricity losses is relatively contemporaneous but not purely driven by short-run dynamics. Therefore, these robustness exercises confirm that the core findings are not sensitive to alternative inference procedures, dynamic lag specifications, or corrections for cross-sectional dependence.

Table 11. Robustness Checks Using Driscoll-Kraay Standard Errors

Variables	(A1)	(A2)	(A3)	(A4)
lnai	-0.0528*** (0.0136)	-0.0302*** (0.0088)	—	—
L1.lnai	—	—	-0.0253** (0.0090)	—
L2.lnai	—	—	—	-0.0215 (0.0123)
Constant	2.2620*** (0.0476)	5.2703*** (0.3662)	5.1946*** (0.4122)	5.0442*** (0.4970)
Controls	No	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
DK SE	Yes	Yes	Yes	Yes
Observations	885	885	826	767
Within R ²	0.028	0.091	0.079	0.070

Notes: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

5.6 Further analysis

5.6.1 Heterogeneity Analysis: AI-Leading vs AI-Following Economies

To explore whether the impact of artificial intelligence varies with technological advancement and electricity structure, we divide the sample into AI-leading, AI-following economies, fossil-fuel dominant economies, diversified renewable-leading economies, and mixed-structure economies and estimate MMQR separately **as shown in Figure 4**. Table 12 presents results for technologically advanced economies, capturing differences in technological maturity, digital infrastructure integration, and absorptive capacity that may condition the effectiveness of AI in improving grid efficiency.

For AI-leading countries, the coefficient on AI is negative and highly significant across all quantiles. Importantly, the magnitude increases monotonically from the lower to upper quantiles, reaching -0.152 at Q90. This pattern suggests that AI exerts a particularly strong loss-reducing effect in high-loss environments within technologically advanced economies. The strengthening impact at upper quantiles implies that where inefficiencies are more pronounced, AI-enabled

optimization and monitoring systems generate substantial efficiency gains. The significant negative scale parameter further indicates that AI reduces dispersion in electricity losses across advanced economies, reinforcing its systemic stabilizing role. In contrast, AI-following countries exhibit a substantially weaker and more heterogeneous effect. Although the location parameter remains negative and significant, the magnitude is considerably smaller, and coefficients at lower quantiles are either insignificant or economically modest. The strengthening effect appears only at higher quantiles (Q75-Q90), suggesting that AI contributes to loss reduction primarily in relatively inefficient segments of developing systems. This attenuated impact is consistent with limited technological absorptive capacity and weaker digital infrastructure integration.

The contrast between AI-leading and AI-following economies highlights a structural complementarity between technological maturity and digital efficiency gains. In advanced economies, AI appears deeply embedded within grid management systems, enabling consistent and strong reductions in electricity losses across the distribution. In developing economies, however, AI adoption may be partial or constrained by institutional and infrastructural limitations, resulting in smaller and less uniform effects. Moreover, these findings indicate that the loss-reducing effect of artificial intelligence is conditional on technological development stages, thereby reinforcing the importance of absorptive capacity and digital ecosystem readiness in translating AI advancement into measurable grid efficiency improvements.

Table 12. Distributional effects of AI on electricity losses: AI leading vs AI following economies

AI-Leading Countries							
Variables	Location	Scale	Q10	Q25	Q50	Q75	Q90
lnAI	-0.112*** (0.016)	-0.025** (0.010)	-0.071*** (0.023)	-0.090*** (0.019)	-0.111*** (0.016)	-0.134*** (0.017)	-0.152*** (0.022)
lnGDP	0.311*** (0.052)	0.036 (0.033)	0.252*** (0.078)	0.279*** (0.062)	0.309*** (0.052)	0.341*** (0.057)	0.367*** (0.071)
lnTRADE	-0.314*** (0.046)	-0.040 (0.029)	-0.248*** (0.068)	-0.278*** (0.054)	-0.312*** (0.046)	-0.348*** (0.050)	-0.377*** (0.062)
lnUBZ	-1.778*** (0.224)	-0.019 (0.140)	-1.747*** (0.334)	-1.761*** (0.265)	-1.778*** (0.225)	-1.795*** (0.246)	-1.809*** (0.302)
lnFDI	-0.111*** (0.040)	0.002 (0.025)	-0.114* (0.059)	-0.113** (0.047)	-0.111*** (0.040)	-0.109** (0.044)	-0.107** (0.054)
Constant	8.356*** (0.640)	0.170 (0.400)	8.076*** (0.952)	8.204*** (0.756)	8.348*** (0.642)	8.501*** (0.701)	8.623*** (0.862)
AI-Following Countries							
lnAI	-0.025*** (0.009)	-0.014*** (0.005)	-0.003 (0.012)	-0.012 (0.010)	-0.024*** (0.009)	-0.038*** (0.009)	-0.046*** (0.011)
lnGDP	-0.206*** (0.019)	0.008 (0.011)	-0.218*** (0.026)	-0.213*** (0.022)	-0.206*** (0.019)	-0.199*** (0.020)	-0.194*** (0.024)
lnTRADE	-0.219*** (0.026)	0.037** (0.015)	-0.277*** (0.037)	-0.252*** (0.031)	-0.220*** (0.026)	-0.185*** (0.028)	-0.162*** (0.033)
lnUBZ	-0.059 (0.072)	0.064 (0.042)	-0.157 (0.103)	-0.114 (0.085)	-0.061 (0.072)	0.000 (0.078)	0.039 (0.092)
lnFDI	0.006 (0.015)	0.043*** (0.009)	-0.059*** (0.021)	-0.031* (0.018)	0.005 (0.015)	0.046*** (0.016)	0.072*** (0.019)
Constant	5.308*** (0.250)	-0.254* (0.147)	5.701*** (0.355)	5.530*** (0.293)	5.316*** (0.251)	5.074*** (0.271)	4.918*** (0.318)

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10.

5.6.2 Heterogeneity Across Electricity Structure Groups

To further examine structural heterogeneity across electricity structure groups, Table 13 reports results for fossil-fuel dominant, diversified renewable-leading, and mixed-structure systems. In fossil-fuel dominant countries, the coefficient on AI is negative and statistically significant across most quantiles, with the magnitude increasing toward the upper tail of the distribution. The effect becomes particularly pronounced at Q75 and Q90, indicating that AI plays a stronger loss-mitigating role in high-loss fossil-based systems. This pattern suggests that traditional grid infrastructures, often characterized by inefficiencies and legacy operational structures, benefit substantially from digital optimization and predictive management. The strengthening impact at higher quantiles implies that AI adoption generates larger marginal efficiency gains where structural inefficiencies are more severe. In contrast, the AI coefficient in diversified renewable-leading countries is statistically insignificant across quantiles. This finding suggests that in systems already characterized by advanced grid integration, diversified energy portfolios, and relatively lower structural losses, the marginal contribution of AI to further loss reduction is limited. In such contexts, efficiency gains may have already been largely internalized through prior technological upgrades, leaving less scope for additional digital improvements to produce measurable reductions in T&D losses. For mixed-structure countries, the results resemble those of the full sample. The coefficient on AI remains negative and statistically significant across all quantiles, with magnitude increasing toward higher-loss environments. This indicates that AI contributes consistently to loss reduction in systems undergoing transitional restructuring, where both fossil-based and renewable components coexist. The distributional pattern suggests that digital technologies are particularly effective in intermediate systems that retain scope for optimization but possess sufficient absorptive capacity to implement AI-based solutions.

Therefore, the heterogeneity results reveal that the effectiveness of artificial intelligence in reducing electricity losses depends critically on the structural composition of the electricity system. AI exhibits the strongest impact in fossil-dominant and mixed systems, where inefficiencies remain more pronounced, while its marginal effect diminishes in highly diversified renewable-leading systems. These findings reinforce the view that technological benefits are contingent on system maturity and structural transition stage, highlighting the importance of aligning digital transformation strategies with electricity system characteristics.

Table 13. Heterogeneity analysis results across electricity structure groups

Fossil-Fuel Dominant Countries							
Variables	Location	Scale	Q10	Q25	Q50	Q75	Q90
lnAI	-0.023*** (-2.85)	-0.007 (-1.28)	-0.014 (-1.08)	-0.017* (-1.65)	-0.023*** (-2.91)	-0.029*** (-3.71)	-0.032*** (-3.66)
lnGDP	-0.196*** (-9.71)	-0.015 (-1.21)	-0.174*** (-5.49)	-0.182*** (-6.96)	-0.196*** (-9.83)	-0.210*** (-10.70)	-0.218*** (-9.85)
lnTRADE	-0.153*** (-4.74)	0.104*** (5.12)	-0.303*** (-5.86)	-0.244*** (-5.86)	-0.148*** (-4.60)	-0.055* (-1.76)	-0.004 (-0.11)
lnUBZ	-0.107 (-1.32)	-0.011 (-0.21)	-0.091 (-0.72)	-0.098 (-0.92)	-0.108 (-1.34)	-0.118 (-1.49)	-0.123 (-1.38)
lnFDI	-0.008 (-0.54)	0.035*** (3.59)	-0.059** (-2.41)	-0.039** (-1.96)	-0.007 (-0.45)	0.024 (1.62)	0.042** (2.48)
Constant	5.173*** (18.59)	0.005 (0.03)	5.166*** (11.86)	5.169*** (14.29)	5.173*** (18.76)	5.177*** (19.10)	5.180*** (16.97)
Diversified Renewable Leading Countries							
Variables	Location	Scale	Q10	Q25	Q50	Q75	Q90

lnAI	-0.002 (0.012)	-0.004 (0.006)	0.004 (0.019)	0.002 (0.017)	-0.003 (0.011)	-0.005 (0.011)	-0.007 (0.011)
lnGDP	-0.336*** (0.074)	-0.118*** (0.039)	-0.144 (0.114)	-0.199* (0.102)	-0.381*** (0.072)	-0.439*** (0.065)	-0.473*** (0.066)
lnTRADE	0.006 (0.096)	0.089* (0.050)	-0.139 (0.150)	-0.098 (0.133)	0.039 (0.091)	0.083 (0.085)	0.109 (0.087)
lnUBZ	-0.920*** (0.243)	0.681*** (0.128)	-2.025*** (0.358)	-1.711*** (0.342)	-0.665** (0.261)	-0.327 (0.206)	-0.132 (0.214)
lnFDI	-0.033 (0.034)	0.006 (0.018)	-0.042 (0.053)	-0.039 (0.047)	-0.031 (0.031)	-0.028 (0.030)	-0.026 (0.031)
Constant	9.573*** (0.776)	-1.867*** (0.408)	12.601*** (1.161)	11.740*** (1.088)	8.872*** (0.809)	7.946*** (0.665)	7.411*** (0.688)

Mixed Structure Countries

Variable	Location	Scale	Q10	Q25	Q50	Q75	Q90
lnAI	-0.056*** (0.007)	-0.015*** (0.004)	-0.034*** (0.009)	-0.043*** (0.007)	-0.056*** (0.007)	-0.070*** (0.008)	-0.079*** (0.009)
lnGDP	-0.214*** (0.022)	0.024* (0.012)	-0.251*** (0.029)	-0.236*** (0.025)	-0.215*** (0.022)	-0.192*** (0.025)	-0.177*** (0.029)
lnTRADE	-0.237*** (0.030)	-0.000 (0.017)	-0.237*** (0.040)	-0.237*** (0.034)	-0.237*** (0.030)	-0.237*** (0.034)	-0.237*** (0.040)
lnUBZ	-0.024 (0.080)	0.117** (0.045)	-0.204* (0.106)	-0.130 (0.090)	-0.026 (0.080)	0.085 (0.090)	0.159 (0.107)
lnFDI	0.004 (0.017)	0.032*** (0.010)	-0.046** (0.022)	-0.026 (0.019)	0.003 (0.017)	0.034* (0.019)	0.054** (0.023)
Constant	5.365*** (0.264)	-0.442*** (0.151)	6.046*** (0.352)	5.768*** (0.298)	5.373*** (0.267)	4.952*** (0.299)	4.672*** (0.354)

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10.

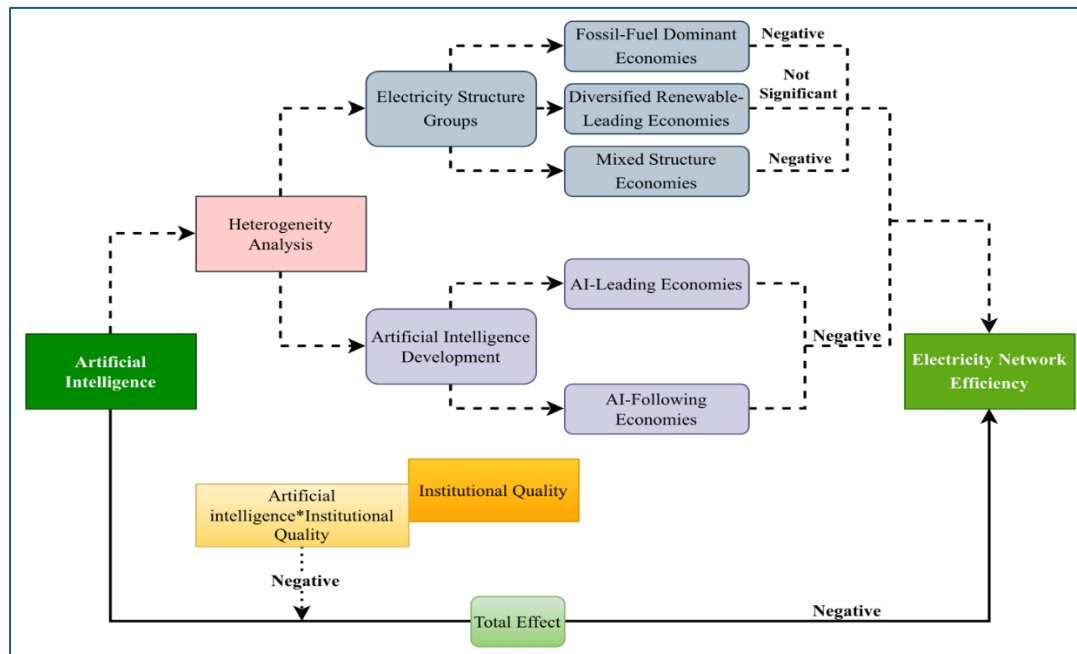


Figure 4: Total effect of artificial intelligence on electricity network efficiency.

6. Discussion and Policy Implications

6.1 Discussion

This study advances a technology-institution complementarity perspective on infrastructure efficiency by demonstrating that the impact of artificial intelligence on electricity transmission and distribution (T&D) losses is both structurally significant and institutionally contingent. Across multiple estimators, distribution-sensitive analyses, and robustness checks, AI development is consistently associated with lower electricity losses. However, beyond establishing a baseline efficiency effect, the findings clarify the conditions under which digital capability translates into operational performance gains.

First, the results challenge the implicit assumption in parts of the digital transformation literature that general-purpose technologies automatically enhance system efficiency once adopted. While AI improves forecasting precision, predictive maintenance, anomaly detection, and real-time dispatch optimization, its effectiveness is not uniform across contexts. The quantile regression results reveal that AI generates larger marginal efficiency gains in high-loss environments, indicating that digital optimization functions as a corrective mechanism where structural inefficiencies are more severe. Rather than simply reinforcing already efficient systems, AI appears to reconfigure coordination mechanisms in contexts characterized by operational friction.

Second, the moderating role of institutional quality provides direct empirical support for the Technology Institution Complementarity Framework. The negative and statistically significant interaction between AI and institutional quality indicates that digital technological capability and governance capacity operate as complementary inputs. In institutional environments characterized by strong regulatory enforcement, transparency, and administrative effectiveness, AI-enabled monitoring and optimization tools are more likely to be effectively implemented and translated into measurable loss reductions. Conversely, in weak institutional settings, technological capability alone does not guarantee efficiency improvements. These findings revise the linear technology → efficiency narrative and demonstrate that digital transformation in infrastructure sectors is conditional on governance alignment.

Third, the heterogeneity analyses further delineate the boundary conditions of digital efficiency gains. Stronger AI effects in AI-leading economies highlight the role of absorptive capacity and technological maturity in amplifying optimization benefits. Similarly, the differentiated effects across electricity structure groups suggest that system composition shapes the marginal returns to digital adoption. AI generates more pronounced efficiency improvements in fossil-dominant and mixed systems, where legacy inefficiencies create greater scope for optimization, while its incremental impact is smaller in diversified renewable-leading systems that have already internalized modernization gains. These results underscore that digital technologies do not operate in isolation but interact with system maturity and structural configuration.

Additionally, the findings extend both technological innovation and institutional economics perspectives. They demonstrate that infrastructure efficiency emerges not from technological adoption alone, nor from governance quality in isolation, but from their alignment. By empirically validating the complementarity mechanism, this study contributes to a more nuanced understanding of how digital transformation reshapes operational performance in complex infrastructure systems.

6.2 Policy Implications

The results carry several policy implications grounded in the complementarity framework. First, digital transformation should be treated as a structural component of grid modernization strategies rather than a peripheral technological upgrade. AI-enabled forecasting systems, predictive maintenance platforms, and anomaly detection tools can generate measurable reductions in electricity losses, particularly in systems characterized by high operational inefficiencies. Targeted digital investments may therefore yield substantial marginal returns in emerging and transitional economies.

Second, technological deployment must be accompanied by institutional strengthening. The moderating analysis indicates that regulatory quality, enforcement credibility, and governance transparency significantly enhance the efficiency gains from AI adoption. Strengthening billing systems, improving anti-theft enforcement, enhancing data governance standards, and ensuring regulatory consistency are critical to unlocking the full operational benefits of digital technologies. Without institutional alignment, technological investments may produce suboptimal or uneven outcomes.

Third, digitalization strategies should account for structural heterogeneity across electricity systems. In fossil-dominant and mixed systems, where optimization potential remains high, AI adoption may deliver particularly strong efficiency improvements. In renewable-leading systems, however, complementary innovations in storage integration, decentralized coordination, and grid flexibility may be necessary to generate additional gains. Policymakers should therefore align digital adoption strategies with system maturity and electricity structure.

Fourth, reducing electricity transmission and distribution losses contributes not only to operational efficiency but also to broader energy security and decarbonization objectives. Lower losses reduce generation requirements, decrease fuel consumption, and enhance the environmental effectiveness of renewable expansion. Within this broader context, artificial intelligence represents a strategic lever for strengthening electrification pathways and advancing long-term carbon neutrality goals, provided that digital capability and institutional capacity evolve in tandem.

7. Conclusion

This study investigates whether artificial intelligence development improves electricity network efficiency, proxied inversely by electricity transmission and distribution losses, and whether institutional quality conditions this relationship. Using an unbalanced panel of 59 countries over the period 2010-2024, the empirical analysis provides robust evidence that AI development is systematically associated with lower electricity losses. The results remain stable across fixed-effects models, instrumental variable generalized method of moments (IV-GMM) estimation, Driscoll-Kraay corrections for cross-sectional dependence, and distribution-sensitive quantile regressions, reinforcing the credibility of the identified relationship.

Beyond establishing a baseline efficiency effect, the study advances a Technology-Institution Complementarity perspective on infrastructure performance. The findings demonstrate that AI does not uniformly reduce electricity losses across contexts; rather, its efficiency effects are structurally conditional. The loss-reducing impact of AI is stronger in high-loss environments, AI-leading economies, and fossil-dominant or mixed electricity systems characterized by greater optimization potential. More importantly, institutional quality significantly amplifies the effect of AI, indicating that governance capacity and digital technological capability operate as complementary inputs in shaping grid efficiency. These results challenge the assumption that

digital transformation automatically generates operational improvements once adopted and instead show that institutional alignment is essential for translating technological capability into measurable performance gains.

By identifying electricity network efficiency, operationalized through transmission and distribution losses, as a grid-level channel through which AI influences energy-system performance, this study contributes to the broader literature on digital transformation and sustainable energy. It integrates technological innovation and institutional economics perspectives to demonstrate that infrastructure efficiency emerges from the interaction between digital capability and governance strength. In doing so, the paper extends existing research beyond aggregate energy and carbon indicators and clarifies the conditions under which digital technologies can meaningfully enhance operational performance.

From a policy standpoint, the results suggest that investments in AI-enabled grid modernization should be accompanied by institutional reforms that strengthen regulatory enforcement, transparency, and administrative coordination. Digitalization strategies that neglect governance capacity may produce uneven or limited efficiency gains. Conversely, coordinated development of technological infrastructure and institutional frameworks can generate significant improvements in grid reliability, energy security, and decarbonization effectiveness.

Several avenues for future research emerge from this analysis. First, micro-level investigations could explore how utility-level governance practices mediate the effectiveness of AI adoption. Second, dynamic analyses could examine long-term feedback effects between digitalization, institutional reform, and infrastructure performance. Third, future work may consider additional infrastructure sectors to assess whether the complementarity mechanism identified here generalizes beyond electricity systems. Such extensions would further clarify how digital transformation reshapes complex socio-technical systems under varying institutional conditions. Sustainable digital transformation in infrastructure systems ultimately depends on the co-evolution of technological capability and institutional alignment.

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