AI Readiness and Governance Quality in Developing Economies: Cross-Sectional and Panel Evidence

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Abstract:

AI readiness is closely associated with governance quality in cross-country rankings, but this relationship does not persist in panel evidence. The 2023 cross-section shows a strong positive association between AI readiness and the Rule of Law, yet the link weakens after controlling for income level and disappears in two-way fixed-effects estimates for 2020–2024. Year-on-year advances in AI readiness do not systematically precede improvements in either the Rule of Law or Control of Corruption. The results suggest that AI readiness indices mainly capture broad development profiles across countries rather than short-run institutional change within countries. International rankings should therefore not be read as leading indicators of governance progress. For developing economies, technological readiness cannot substitute for foundational institutional capacity.

Keywords: AI readiness; governance quality; institutional capacity; developing economies; panel fixed effects.

Jel Classification Codes: O33; O38; O43; C33; H11.

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1. Introduction :

Artificial intelligence readiness has become an increasingly visible benchmark in development policy and economic governance. Governments and international organisations use AI readiness rankings to compare national digital capacity, infrastructure preparedness and institutional conditions for technological transformation. Recent empirical studies have extended this discussion from advanced economies to developing and emerging economies, linking AI readiness and digital infrastructure to economic growth, banking transformation, innovation performance, sustainable development and public governance (Ouakil et al., 2026; Patra et al., 2026; Sitnicka et al., 2025; Zheng et al., 2025). In this literature, AI readiness is often treated not only as a technological indicator but also as a signal of broader institutional and administrative capacity.

A recurring empirical pattern supports this interpretation. Countries with higher AI readiness scores tend to report stronger rule of law, better corruption control, more effective administration and more developed regulatory environments. Studies on African economies, BRICS-Plus countries and emerging markets suggest that AI-related capacity is more likely to generate economic, social or environmental gains when governance quality, regulatory capacity or institutional adaptability is stronger (Bergougui, 2026; Mahmood et al., 2026; Mansour et al., 2026; Ouakil et al., 2026). The policy narrative is intuitive: capable institutions support AI deployment, while digital systems may improve transparency, service delivery and administrative efficiency.

However, this cross-sectional association is highly confounded by omitted development characteristics. Developing economies differ sharply in income level, long-run institutional capacity, infrastructure quality and administrative depth. These factors move together. Countries with higher income and stronger historical institutions are more likely to invest in digital infrastructure, obtain higher AI readiness scores and receive better governance assessments. The observed relationship between AI readiness and governance quality may therefore capture between-country development profiles rather than a short-run link between technological readiness and institutional improvement.

Beyond identification, existing empirical designs face construct-contamination concerns. The Oxford Insights Government AI Readiness Index (GARI), one of the most widely used cross-country AI readiness measures, includes government-pillar indicators that overlap directly with the Worldwide Governance Indicators (WGI), including Regulatory Quality, Government Effectiveness and Voice and Accountability. If the composite GARI score is regressed against WGI outcomes, the estimates suffer from mechanical circularity. This problem is especially relevant because recent AI readiness studies increasingly combine readiness indices with governance or institutional indicators without always separating technological capacity from institutional components (Irikefe et al., 2026; Köseoglu et al., 2026; Yao et al., 2026).

This study addresses both issues by constructing a Clean AI Readiness Index (CAIRI), defined as the average of the Technology Sector and Data and Infrastructure pillars of GARI. The Government pillar is excluded in full. CAIRI therefore captures technology-sector capacity, digital infrastructure and data readiness without directly importing WGI governance scores. We then compare cross-sectional evidence with panel fixed-effects evidence for developing economies. While the study does not exploit a strictly exogenous shock, the two-way fixed-effects design isolates within-country temporal variation from cross-sectional sorting by absorbing country-specific and year-specific heterogeneity.

The study is guided by two research questions:

RQ1. Is clean AI readiness associated with governance quality in developing economies in cross-sectional comparisons?

RQ2. Does the AI readiness–governance association persist when within-country variation is examined over time?

The empirical analysis combines a 2023 cross-section of 139 developing economies with an unbalanced panel of 120 countries over 2020–2024. Rule of Law and Control of Corruption are used as the main governance outcomes. Cross-sectional OLS estimates are compared with two-way fixed-effects models. The results show a clear contrast. CAIRI is positively associated with Rule of Law in the 2023 cross-section, but the association weakens after accounting for income level and disappears in the panel fixed-effects estimates. Year-on-year changes in CAIRI are not systematically associated with year-on-year changes in either Rule of Law or Control of Corruption.

The paper makes three contributions. First, it provides a non-circular AI readiness measure for studies using WGI governance outcomes. Second, it shows that the AI readiness–governance relationship differs sharply between cross-sectional and within-country settings. Third, it focuses on developing economies, where AI readiness rankings are increasingly used in policy discussion but where income-level and institutional differences are especially pronounced. The paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 describes the data, variables and estimation strategy. Section 4 presents the empirical results. Section 5 discusses the interpretation, limitations and implications of the findings.

2. Literature Review and Hypothesis Development

2.1 AI Readiness as a Composite National Capability

AI readiness describes whether a country has the technological, infrastructural and institutional conditions required to absorb artificial intelligence. Unlike single indicators such as broadband penetration, AI patents or digital skills, readiness indices combine multiple layers of national capacity: data infrastructure, human capital,

innovation systems, policy preparedness and administrative capability. This composite structure is useful for cross-country comparison, but it also creates interpretive ambiguity because composite indicators often merge inputs, capabilities and outcomes into a single score (Greco et al., 2019; Wirtz et al., 2019).

This ambiguity becomes more serious when AI readiness is used to explain governance quality. A composite index that embeds institutional indicators cannot be treated as a purely technological variable. If governance components enter the explanatory index and governance outcomes subsequently serve as dependent variables, the estimated association may partly reflect construct contamination rather than an independent empirical relationship. This concern is central to studies using the Oxford Insights Government AI Readiness Index with the Worldwide Governance Indicators, because the Government pillar of GARI includes governance-related components while the Technology Sector and Data and Infrastructure pillars are closer to the digital-capacity dimension of AI readiness (Kaufmann et al., 2010; Sun & Medaglia, 2019).

Empirically, national AI capability does not operate in an institutional vacuum. Its returns are conditioned by regulatory capacity, organisational readiness, financial stability and institutional adaptability. Recent work links AI-related capacity to growth, employment, renewable energy, ESG performance and innovation, but the gains are usually mediated by governance quality or implementation capacity rather than generated by technology alone (Saba & Ngepah, 2024; Liu et al., 2025; Mansour et al., 2026; Zheng et al., 2025). This conditional nexus creates a methodological requirement: technological readiness must be separated from the institutional and developmental content already embedded in country-level indices.

2.2 Governance Quality and Institutional Persistence

Governance quality is a persistent feature of development. Institutional economics treats property rights, rule enforcement, bureaucratic credibility and constraints on predation as foundations of long-run economic performance (North, 1990; Acemoglu et al., 2001). Later work shows that contemporary development outcomes remain strongly shaped by historically embedded institutional and political conditions (Rodrik et al., 2004). Consequently, baseline digital deployment and institutional indicators may simply co-move along the same long-run development trajectory, confounding short-run evaluation.

The Worldwide Governance Indicators are widely used to measure institutional quality across countries. Rule of Law captures perceptions of contract enforcement, property rights, courts and public security, while Control of Corruption measures the extent to which public power is used for private gain (Kaufmann et al., 2010). Their broad coverage makes them useful for comparative analysis, but their perception-based construction and high persistence limit their ability to capture rapid institutional change. Governance indicators may also absorb income and development narratives, producing circular hierarchies in cross-country regressions (Kurtz & Schrank, 2007).

For developing economies, the identification problem is sharper. Countries differ not only in current AI readiness but also in administrative depth, fiscal capacity, education systems, regulatory credibility and infrastructure quality. These characteristics jointly shape both readiness scores and governance outcomes. A positive cross-sectional coefficient on AI readiness may therefore capture omitted development characteristics rather than a direct link between technological capacity and institutional improvement. Recent work on emerging economies similarly treats institutional quality as part of a wider development structure rather than an isolated policy lever (Malik & Sah, 2024; Bergougui, 2026).

2.3 Digital Technology and the Governance Channel

A positive AI readiness–governance relationship remains theoretically plausible. Digital systems can reduce administrative discretion, improve traceability, expand access to information and strengthen transparency in procurement, taxation and licensing. E-government research shows that technology can reshape public administration when it changes information flows and reduces discretionary bottlenecks (Bhatnagar, 2004). ICT-based transparency tools may also support anti-corruption capacity by improving openness and citizen monitoring (Bertot et al., 2010). Evidence from cross-country studies further suggests that e-government development can reduce corruption when supported by institutional capacity (Andersen, 2009; Elbahnasawy, 2014).

AI readiness may deepen these mechanisms where data systems and digital infrastructure are sufficiently developed. Governments with stronger digital foundations may be better positioned to automate routine decisions, detect fraud patterns and improve service delivery. Yet this technological transmission is inherently non-automatic. Institutional parameters, budgetary depth, data governance and political incentives determine whether digital tools become instruments of accountability or simply new administrative layers. Public-sector AI studies therefore emphasise implementation capacity, accountability design and administrative readiness as central conditions for effective use (Criado & Gil-Garcia, 2019; Mergel et al., 2019).

Recent empirical evidence points in the same direction. Governance quality moderates the relationship between AI and growth or employment in emerging-economy settings, while institutional quality shapes the effect of AI on renewable energy and sustainability outcomes (Saba & Ngepah, 2024; Zheng et al., 2025). In corporate settings, AI adoption is associated with ESG or governance-related performance only when implementation capacity, disclosure quality and organisational controls are present (Wang et al., 2025; Xie & Wu, 2025). The implication is that AI readiness may correlate with governance quality, but the mechanism is unlikely to be mechanical or immediate.

2.4 Cross-Sectional Association and Within-Country Evidence

The central empirical issue is the distinction between between-country association and within-country change. Cross-sectional designs can show whether countries with higher AI readiness also display stronger governance quality. They are weaker at separating AI readiness from income, infrastructure and institutional characteristics that jointly determine both variables. Country fixed effects address this problem by absorbing stable national characteristics such as geography, legal tradition, historical institutions and long-run development level. Year fixed effects further absorb common shocks and global measurement trends.

This distinction has become increasingly important as AI research moves from descriptive readiness rankings to panel-based evidence. Studies of AI and governance, ESG, environmental transition and financial performance now more often use panel methods, GMM estimators or quasi-experimental designs to exploit temporal variation rather than rely only on cross-sectional comparisons (Ouakil et al., 2026; Wang et al., 2025; Awwad, 2026). Existing panel frameworks, however, rarely test whether a de-contaminated AI readiness measure tracks genuine within-country institutional shifts. The relationship between clean AI readiness and short-run governance change therefore remains unresolved.

This study advances two hypotheses:

H1. Clean AI readiness is positively associated with governance quality in cross-sectional comparisons among developing economies.

H2. The cross-sectional association between clean AI readiness and governance quality attenuates or vanishes once within-country temporal variation is isolated.

3. Data and Methodology

3.1 Data Sources and Sample Construction

The empirical analysis integrates three country-level data streams: the Oxford Insights Government AI Readiness Index (GARI), the World Bank Worldwide Governance Indicators (WGI), and the World Bank World Development Indicators (WDI). GARI provides annual dimensions of national AI readiness, WGI supplies the institutional outcome measures, and WDI provides structural macroeconomic controls (Oxford Insights, 2024; Kaufmann et al., 2010; World Bank, 2024b, 2024c). The design separates technological and infrastructural AI readiness from governance content embedded in composite readiness scores.

The estimation sample is restricted to developing economies, defined under the World Bank income classification as low-income, lower-middle-income and upper-middle-income countries (World Bank, 2024a). High-income economies are excluded to focus on the development-policy setting in which AI readiness rankings are often interpreted as signals of institutional upgrading. The cross-sectional baseline contains 139 developing economies in 2023. The temporal analysis uses a 2020–2024 panel of 120 countries with complete core

observations for clean AI readiness, Rule of Law and GDP per capita, yielding 558 country-year observations in the main panel specification.

3.2 Construction of the Clean AI Readiness Index

The primary explanatory variable is the Clean AI Readiness Index, denoted as $\mathrm{CAIRI}_{\mathrm{it}}$. It is constructed from the non-governmental dimensions of the GARI framework. The Government pillar is excluded, and the remaining two pillars are averaged as follows:

$$\mathrm{CAIRI}_{\mathrm{it}} = \frac{\text{Technology Sectorit} + \text{Data and Infrastructureit}}{2}, \quad (1)$$

where Technology Sectorit and Data and Infrastructureit are the official GARI pillar scores for country i in year i, each ranging from 0 to 100. The exclusion of the Government pillar is substantive. That pillar incorporates governance-related inputs, including WGI-based indicators such as Regulatory Quality and Government Effectiveness. Using the full GARI score to explain WGI governance outcomes would induce construct contamination and mechanical circularity. CAIRI isolates the technology-sector and data-infrastructure dimensions of AI readiness while avoiding direct overlap with WGI-based institutional measures.

Two auxiliary specifications assess the stability of the index construction. First, the Technology Sector and Data and Infrastructure pillars are entered separately to examine whether the association is concentrated in one component. Second, a principal component analysis weighted version of $CAIRI_{it}$ is used as an alternative aggregation rule. The simple average remains the baseline because it is transparent, replicable and invariant to sample-specific loading structures.

3.3 Governance Outcomes and Control Variables

The dependent variables are Rule of Law and Control of Corruption from WGI. Rule of Law captures perceptions of contract enforcement, property rights, courts, policing and civic security, while Control of Corruption captures perceptions of the use of public authority for private gain (Kaufmann et al., 2010; World Bank, 2024c). Both indicators are standard measures in cross-country institutional research and align with the governance mechanisms through which digital and AI-enabled systems may affect accountability, enforcement and administrative credibility (North, 1990; Rodrik et al., 2004).

The control vector captures structural development conditions that may co-determine technological deployment and institutional trajectories. Economic capacity is measured by the natural logarithm of PPP-adjusted constant 2017 GDP per capita. General digital diffusion is captured by the share of individuals using the internet. Urban population share accounts for spatial concentration and administrative reach. Trade openness captures

external economic integration, while total population is included in logarithmic form in the full-control specifications. These indicators are obtained from WDI (World Bank, 2024b).

Table 1 summarises the variables, measurement definitions and data sources used in the empirical analysis. The table clarifies the separation between AI readiness inputs, governance outcomes and structural controls, which is central to the paper's identification strategy.

Table N°1: Variable Definitions and Data Sources

Variable	Definition	Source	Role
CAIRI	Average of GARI Technology Sector and Data & Infrastructure pillar scores, scaled 0–100	Oxford Insights GARI	Main IV
CAIRI – Tech	GARI Technology Sector pillar score, scaled 0–100	Oxford Insights GARI	Pillar IV
CAIRI – Data	GARI Data & Infrastructure pillar score, scaled 0–100	Oxford Insights GARI	Pillar IV
Rule of Law	WGI estimate of contract enforcement, property rights, courts, policing and public security	World Bank WGI	Main DV
Control of Corruption	WGI estimate of the use of public authority for private gain	World Bank WGI	Secondary DV
Regulatory Quality	WGI estimate of regulatory capacity; used only as supplementary reference because it overlaps with GARI Government pillar	World Bank WGI	Supplementary
Log GDP per capita	Natural log of PPP-adjusted GDP per capita, constant 2017 USD	World Bank WDI	Control
Internet users	Share of individuals using the internet	World Bank WDI	Control
Urban population	Share of population living in urban areas	World Bank WDI	Control
Trade openness	Exports plus imports as a percentage of GDP	World Bank WDI	Control

Note: CAIRI excludes the GARI Government pillar to avoid overlap with WGI governance inputs. Developing economies follow World Bank income classification.

3.4 Cross-Sectional Specification

The first empirical test estimates the baseline between-country association in 2023. The ordinary least squares specification is:

$$\text{Governance}_{i,2023} = \alpha + \beta \text{CAIRI}_{i,2023} + X'_{i,2023}\delta + \varepsilon_i, \qquad (2)$$

where $\text{Governance}_{i,2023}$ is either Rule of Law or Control of Corruption for country i, $\text{CAIRI}_{i,2023}$ is the cleaned AI readiness score, and $X_{i,2023}$ denotes the vector of structural controls. The coefficient β identifies the cross-sectional sorting effect between AI readiness and governance quality. Heteroskedasticity-consistent HC3

standard errors are used to account for arbitrary variance differences across developing economies with heterogeneous income and institutional profiles (Long & Ervin, 2000).

This specification tests whether higher-readiness countries also exhibit stronger governance quality. It does not absorb stable national traits such as legal tradition, historical institutions or long-run development level. The cross-sectional model therefore functions as the benchmark against which the stricter within-country estimates are evaluated.

3.5 Panel Fixed-Effects Specification

The second empirical test examines whether the cross-sectional association survives after stable country characteristics and common year shocks are removed. The two-way fixed-effects specification is:

$$\text{Governanceit} = \alpha_i + \gamma_t + \beta\text{CAIRIit} + \text{Xit}'\delta + \varepsilon\text{it}, \quad (3)$$

where α_i denotes country fixed effects and γ_t denotes year fixed effects. Country fixed effects absorb time-invariant national characteristics, including geography, legal origin, historical institutions and stable development differences. Year fixed effects absorb global shocks and common measurement shifts. Conditional on these fixed effects, β is identified from within-country temporal deviations in clean AI readiness.

Standard errors are clustered at the country level to allow arbitrary serial correlation and heteroskedasticity within national panels (Wooldridge, 2010; Cameron & Miller, 2015). In the absence of an exogenous policy shock or external instrumental variable, β is interpreted as a conditional within-country association. This interpretation is sufficient for the paper's central test: whether AI readiness contains governance-related predictive content after cross-sectional development sorting is removed.

3.6 Robustness Checks

Three robustness checks assess whether the findings depend on functional form, panel composition or index aggregation. First, a first-difference specification removes time-invariant country heterogeneity through differencing rather than demeaning:

$$\Delta\text{Governanceit} = \beta\Delta\text{CAIRIit} + \Delta\text{Xit}'\delta + \Delta\varepsilon\text{it}. \quad (4)$$

Second, the two-way fixed-effects model is re-estimated on the balanced subsample of countries observed continuously over 2020–2024. This check limits the influence of changing panel composition. Third, the baseline CAIRI_{it} measure is replaced with the PCA-weighted alternative to test whether the results depend on the simple-average aggregation rule.

The empirical design follows the structure of the research questions. The cross-sectional model evaluates whether clean AI readiness is associated with governance quality across developing economies. The fixed-effects

and first-difference models test whether that association attenuates once the analysis shifts from between-country comparison to within-country variation.

4. Results and Discussion

4.1 Descriptive Pattern and Developmental Sorting

Table N°2: Descriptive Statistics and Correlations, 2023

#	Variable	N	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	CAIRI	139	36.10	9.59	9.78	67.76	1								
2	CAIRI – Tech	139	26.90	8.09	14.27	60.76	0.91***	1							
3	CAIRI – Data	139	45.30	12.28	5.29	74.75	0.96***	0.76***	1						
4	Rule of Law	139	-0.63	0.68	-2.00	1.20	0.46***	0.33***	0.50***	1					
5	Control of Corruption	139	-0.60	0.61	-1.88	1.36	0.43***	0.30***	0.47***	0.90***	1				
6	GDP per capita	133	10,438.30	8,087.25	1,036.17	35,069.20	0.76***	0.66***	0.79***	0.33***	0.35***	1			
7	Internet users	124	58.52	25.18	7.17	97.69	0.76***	0.69***	0.75***	0.44***	0.39***	0.79***	1		
8	Urban population	139	51.30	19.66	15.06	92.68	0.50***	0.50***	0.45***	0.10	0.12	0.55***	0.67***	1	
9	Trade openness	136	61.14	32.57	21.46	258.56	0.15*	0.13	0.15*						

Note: Lower triangle reports Pearson correlations. GDP per capita is in constant 2017 PPP USD and logged in regressions. * p < 0.10, ** p < 0.05, *** p < 0.01.

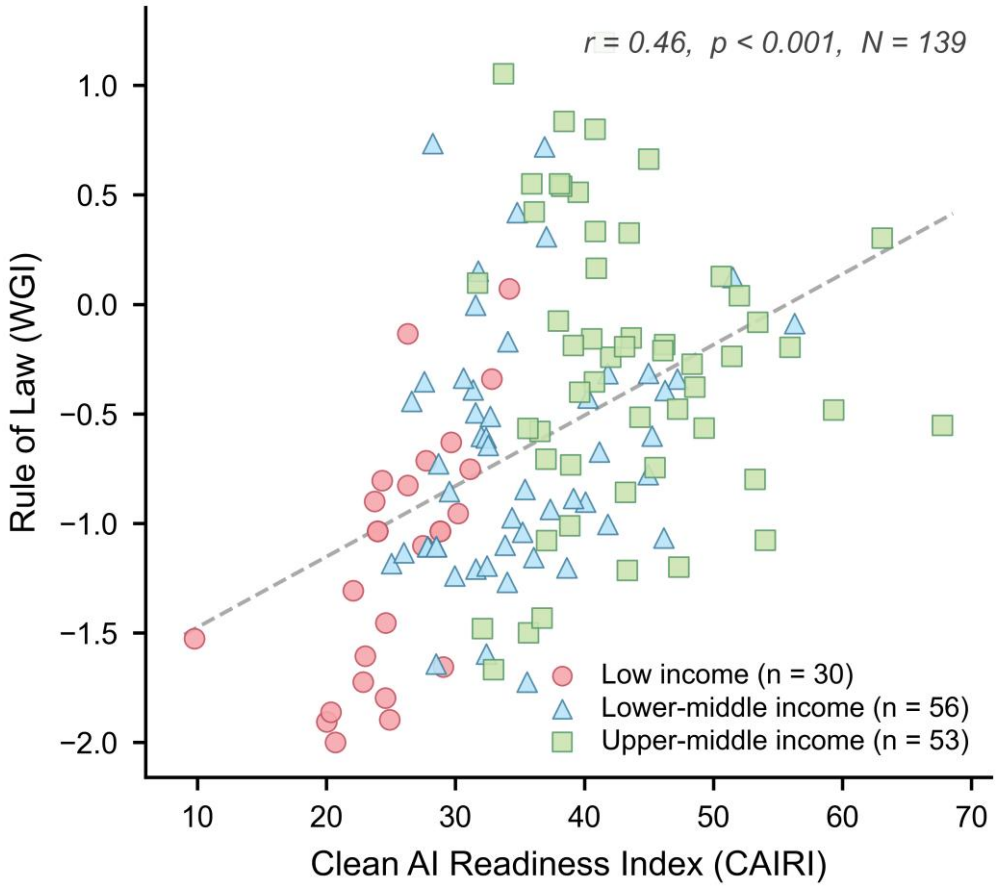
Table 2 reports the descriptive statistics and pairwise correlations for the 2023 cross-section. The unconditioned association between clean AI readiness and governance quality is positive: CAIRI correlates with Rule of Law at $r = 0.46$ and with Control of Corruption at $r = 0.43$, both statistically significant at conventional levels. This raw pattern is consistent with the conventional view that countries with stronger digital and AI-related capacity also tend to display stronger institutional quality.

The same correlation matrix identifies the main source of confounding. $CAIRI$ is also strongly correlated with log GDP per capita and internet penetration, both at $r = 0.76$.These magnitudes suggest that technological readiness is embedded in a broader development profile. Economies with higher income levels tend to have stronger digital infrastructure, deeper administrative capacity and higher governance scores. This pattern is consistent with institutional-development arguments that governance, infrastructure and income evolve as a

bundled national-capacity profile rather than as isolated short-run variables (Acemoglu et al., 2001; Rodrik et al., 2004).

Figure 1 visualises this developmental sorting. Although the fitted line between $CAIRI$ and Rule of Law is positive, the scatter plot is clearly stratified by World Bank income group. Low-income economies cluster at low levels of both AI readiness and governance quality, while upper-middle-income economies occupy a higher and wider range. The visual evidence reinforces the diagnostic implication of Table 2: the cross-sectional covariance is present, but it is heavily conditioned by development-level sorting.

Fig N°1: Clean AI Readiness and Rule of Law, 2023



Note: Points are grouped by World Bank income category. The dashed line shows the fitted cross-sectional relationship. CAIRI = Clean AI Readiness Index.

4.2 Cross-Sectional Evidence

Table 3 presents the cross-sectional OLS estimates for the 2023 baseline. The bivariate specification in Model 1 provides initial support for H1. $CAIRI$ is positively associated with Rule of Law, with a coefficient of $\beta = 0.032$ and a standard error of $SE = 0.005$.

The association attenuates once income is introduced. In Model 2, the preferred cross-sectional benchmark, controlling for log GDP per capita reduces the $CAIRI$ coefficient to $\beta = 0.018$ with $SE = 0.010$, moving the

estimate below the conventional 5% significance threshold. The decline is substantively important because income absorbs part of the unconditioned association. The result indicates that cross-country digital readiness partly reproduces underlying development hierarchies rather than isolating an autonomous institutional transmission channel (Kurtz & Schrank, 2007).

Table N°3: Cross-Sectional OLS Estimates, 2023

Model	Dependent variable	Main IV	N	Adj. R^2	β (SE)	Controls
M1	Rule of Law	CAIRI	139	0.202	0.032*** (0.005)	None
M2	Rule of Law	CAIRI	133	0.150	0.018* (0.010)	Log GDP per capita
M3	Rule of Law	CAIRI	122	0.598	0.057*** (0.008)	Log GDP, internet, trade, urban, log population
M4	Control of Corruption	CAIRI	122	0.178	0.011 (0.009)	Log GDP, internet, trade, urban
M5	Rule of Law	CAIRI – Tech	122	0.256	0.008 (0.009)	Log GDP, internet, trade, urban
M6	Rule of Law	CAIRI – Data	122	0.276	0.015** (0.007)	Log GDP, internet, trade, urban
M7	Rule of Law	CAIRI – PCA	121	0.257	0.011 (0.007)	Log GDP, internet, urban

Note: OLS estimates with HC3 robust standard errors in parentheses. M2 is the conservative benchmark. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The full-control specification in Model 3 produces a larger and statistically significant coefficient, but this shift reflects a suppressor pattern rather than a stronger substantive relationship. Internet penetration is highly collinear with $CAIRI$ and removes a major component of digital diffusion from the readiness measure once both variables are included. The remaining coefficient captures residual variation in the readiness construct rather than the overall cross-country readiness profile. For this reason, the preferred cross-sectional inference rests on Model 2: the link between clean AI readiness and Rule of Law is positive but fragile once income differences are extracted.

The Control of Corruption models produce a more restrictive conclusion. The corresponding $CAIRI$ coefficients are statistically indistinguishable from zero across the baseline specifications. This cross-outcome asymmetry is theoretically coherent. Technological readiness is more closely aligned with formal administrative capacity and rule-enforcement infrastructure than with corruption control, which depends on political incentives, discretionary enforcement and accountability constraints. Recent e-governance evidence similarly shows that digital transparency tools reduce corruption only when embedded in stronger institutional and administrative settings (Seiam, 2024; Mudey et al., 2026). H1 therefore receives conditional support: the association is visible in raw cross-country comparison, but it weakens once development level is accounted for.

4.3 Panel Fixed-Effects Evidence

Table 4 reports the within-country test. Once country and year fixed effects are included, the AI readiness–governance association is neutralised. In the primary panel specification for Rule of Law, conditioning on country

fixed effects, year fixed effects and time-varying income leaves the *CAIRI* coefficient close to zero and statistically insignificant. The same pattern holds after adding the full set of time-varying controls, replacing Rule of Law with Control of Corruption, and decomposing *CAIRI* into its Technology Sector and Data and Infrastructure pillars.

This parameter neutralisation constitutes the central empirical insight of the study. Cross-sectional OLS estimates draw identification from long-run differences across countries, while the two-way fixed-effects model relies on within-country temporal deviations. The absence of a significant within-country β indicates that year-on-year changes in clean AI readiness do not map into systematic improvements in governance quality over the 2020–2024 window.

Table N°4: Panel Fixed-Effects and Robustness Estimates, 2020–2024

Model	Estimator	Dependent variable	Main IV	Obs.	Countries	β (SE)	Within R^2	Controls
M1	Two-way FE	Rule of Law	CAIRI	581	125	-0.001 (0.003)	0.005	None
M2	Two-way FE	Rule of Law	CAIRI	558	120	-0.002 (0.002)	-0.050	Log GDP
M3	Two-way FE	Rule of Law	CAIRI	519	113	-0.001 (0.002)	0.079	Log GDP, internet, urban, trade
M4	Two-way FE	Control of Corruption	CAIRI	558	120	0.001 (0.002)	-0.028	Log GDP
M5	Two-way FE	Control of Corruption	CAIRI	519	113	0.002 (0.002)	-0.004	Log GDP, internet, urban, trade
M6	Two-way FE	Rule of Law	CAIRI – Tech	558	120	-0.001 (0.003)	-0.051	Log GDP
M7	Two-way FE	Rule of Law	CAIRI – Data	558	120	-0.001 (0.001)	-0.060	Log GDP
M-LIC	Subsample FE	Rule of Law	CAIRI	91	19	0.005 (0.004)	0.124	Log GDP
M-LMIC	Subsample FE	Rule of Law	CAIRI	235	49	-0.003 (0.003)	-0.012	Log GDP
M-UMIC	Subsample FE	Rule of Law	CAIRI	232	52	-0.003 (0.004)	-0.098	Log GDP
FD-RL	First difference	Δ Rule of Law	Δ CAIRI	438	123	0.001 (0.001)	0.062	Δ Log GDP
FD-CC	First difference	Δ Control of Corruption	Δ CAIRI	438	123	-0.000 (0.001)	0.000	Δ Log GDP

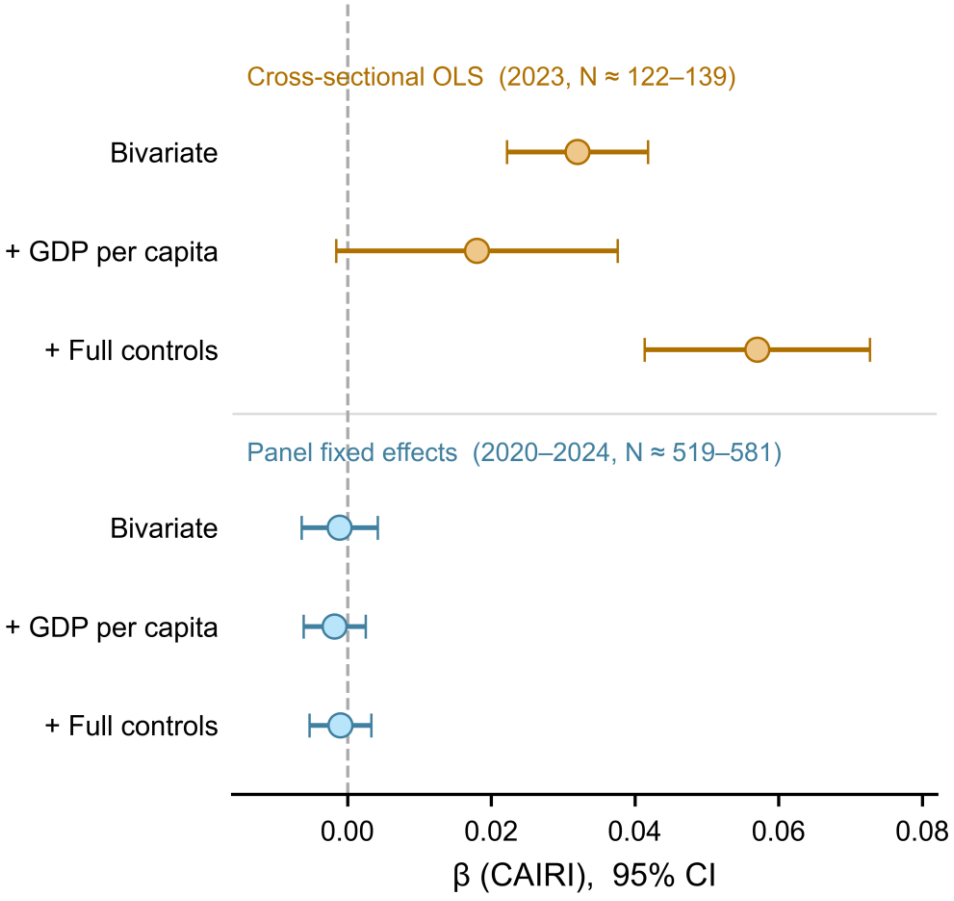
Note: Two-way FE models include country and year fixed effects with country-clustered standard errors. FD models use HC3 robust standard errors. No CAIRI coefficient is statistically significant.

Figure 2 summarises the contrast. The cross-sectional point estimates lie above zero, whereas the panel estimates cluster around the null, with 95% confidence intervals crossing zero. This divergence marks the empirical boundary of AI readiness rankings. They classify countries along long-run development profiles, but they do not

function as short-run leading indicators of institutional upgrading. This pattern supports H2: the cross-sectional association between clean AI readiness and governance quality attenuates or vanishes once within-country temporal variation is isolated.

The finding is consistent with institutional persistence and conditional digital-return arguments. Governance architectures adjust slowly, especially over a five-year horizon. Digital infrastructure and data-readiness scores may change more rapidly through investment and policy prioritisation, but rule enforcement and corruption control are constrained by bureaucratic, legal and political equilibria. Cross-country panel evidence similarly suggests that digital-governance gains depend on administrative quality, anti-corruption capacity and political stability rather than emerging mechanically from technology adoption (Zhao & Du, 2025). The panel null therefore does not negate the relevance of AI readiness. It restricts its interpretation: readiness scores are structural benchmarks, not evidence of immediate institutional change.

Fig N°2: Cross-Sectional and Panel Estimates of CAIRI



Note: Points report CAIRI coefficients with 95% confidence intervals. Cross-sectional models use 2023 OLS estimates; panel models use 2020–2024 two-way fixed effects.

4.4 Robustness and Appendix Evidence

The panel null is stable across alternative specifications. Re-estimating the two-way fixed-effects models within separate World Bank income groups yields no statistically significant $CAIRI$ coefficients for low-income, lower-middle-income or upper-middle-income economies. The aggregate result is therefore not driven by offsetting income-group effects.

The first-difference estimates confirm the same pattern. Changes in clean AI readiness are not systematically associated with changes in Rule of Law or Control of Corruption. Appendix Figure A1 provides the visual counterpart. Panel A shows heterogeneous upward movements in $CAIRI$ across countries and income groups during 2020–2024, while Panel B plots $\Delta\,\mathrm{CAIRI}_{it}$ against $\Delta\,\mathrm{Rule\ of\ Law}_{it}$. The absence of a visible slope in the first-difference plot supports the fixed-effects evidence: short-run gains in clean AI readiness do not coincide with measurable short-run governance improvement.

The result is also robust to panel composition and index aggregation. Restricting the sample to countries observed continuously over 2020–2024 does not change the inference. Replacing the simple-average $CAIRI$ with the PCA-weighted alternative also fails to recover a significant within-country association. The empirical boundary is therefore not an artifact of missing-data structure, sample composition or index-weighting choice.

Taken together, the results distinguish benchmarking from prediction. Clean AI readiness is informative for locating countries within a broad development hierarchy. It summarises digital infrastructure, technology-sector capacity and data foundations that are closely related to income and institutional depth. It is much weaker as a short-run indicator of governance change. For developing economies, the implication is direct: improving AI readiness may support a wider modernisation agenda, but it cannot substitute for the slower institutional work required to strengthen rule enforcement, administrative credibility and corruption control.

5. Conclusion:

This study re-evaluates the relationship between national AI readiness and public governance quality in developing economies. By constructing a de-contaminated readiness measure from the non-governmental pillars of the Government AI Readiness Index, the analysis separates technological and infrastructural capacity from pre-existing administrative and institutional inputs.

The estimates draw a clear empirical boundary between cross-country sorting and within-country co-movement. In the 2023 cross-section, clean AI readiness is positively associated with Rule of Law, but the association weakens once income differences are accounted for. In the 2020–2024 two-way fixed-effects panel, the relationship is neutralised. Year-on-year improvements in clean AI readiness do not systematically translate into short-run gains in Rule of Law or Control of Corruption. This null result remains stable across first-difference estimates, income-group subsamples, balanced-panel specifications and PCA-weighted index construction. The

observed cross-country alignment is therefore better understood as a product of long-run development bundling than as evidence of a direct high-frequency technological transmission channel.

International AI readiness rankings should consequently be read as structural benchmarking tools, not as predictive indicators of institutional upgrading. They capture meaningful differences in technological capacity, data infrastructure and digital foundations, but these dimensions remain deeply tied to income level, administrative depth and broader state capacity. For policymakers in developing economies, improving AI readiness may support a wider modernisation agenda, but it cannot substitute for the slower institutional work required to strengthen rule enforcement, administrative credibility and corruption control.

The relatively short panel window reflects the recent availability of comparable AI readiness data, but it also establishes a necessary short-run baseline for future research. Subsequent studies may extend the time horizon, exploit policy discontinuities or use sector-level administrative evidence to test where AI readiness produces measurable governance change. The present evidence cautions against conflating technological adoption with institutional modernisation. In developing economies, AI capacity and governance quality remain connected, but their connection is primarily structural rather than immediate.

5. List of references:

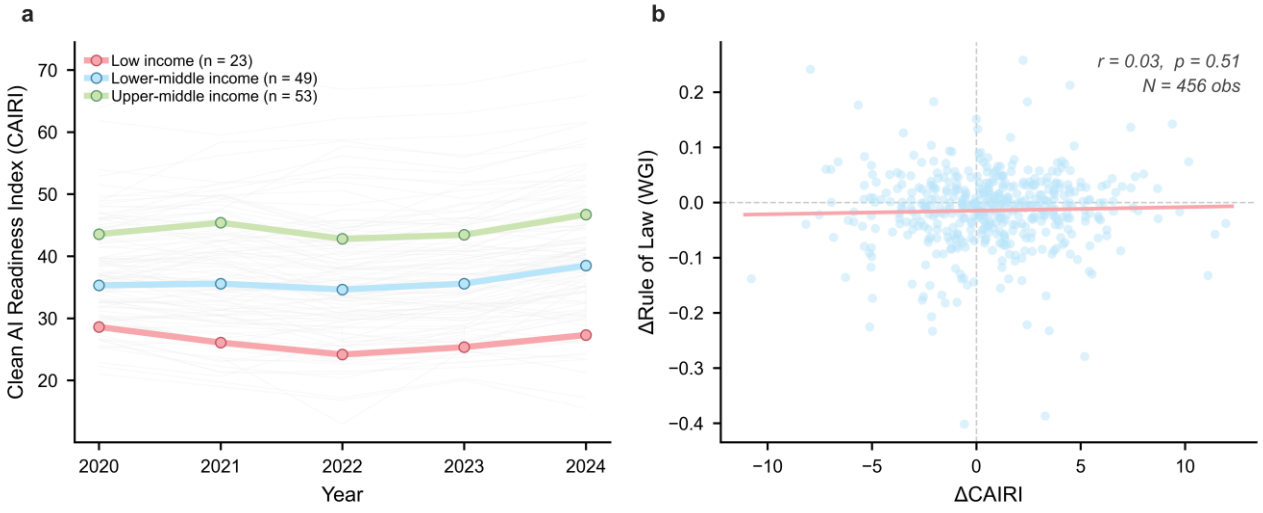
1. Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The colonial origins of comparative development: An empirical investigation. *American Economic Review, 91*(5), 1369–1401. https://doi.org/10.1257/aer.91.5.1369
2. Andersen, T. B. (2009). E-government as an anti-corruption strategy. *Information Economics and Policy, 21*(3), 201–210. https://doi.org/10.1016/j.infoecopol.2008.11.003
3. Awwad, B. (2026). Does generative artificial intelligence reinforce financial performance? The mediating role of governance quality in emerging markets. *Future Business Journal, 12*(1), Article 39. https://doi.org/10.1186/s43093-025-00707-3
4. Bergougui, B. (2026). Can artificial intelligence technologies advance environmental sustainability? The role of institutional adaptability and skill-biased technological transformation. *Sustainable Development, 34*(2), 222–244. https://doi.org/10.1002/sd.70296
5. Bertot, J. C., Jaeger, P. T., & Grimes, J. M. (2010). Using ICTs to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. *Government Information Quarterly, 27*(3), 264–271. https://doi.org/10.1016/j.giq.2010.03.001
6. Bhatnagar, S. (2004). *E-government: From vision to implementation: A practical guide with case studies*. SAGE Publications.
7. Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources, 50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317
8. Criado, J. I., & Gil-Garcia, J. R. (2019). Creating public value through smart technologies and strategies: From digital services to artificial intelligence and beyond. *International Journal of Public Sector Management, 32*(5), 438–450. https://doi.org/10.1108/IJPSM-07-2019-0178
9. Elbahnasawy, N. G. (2014). E-government, internet adoption, and corruption: An empirical investigation. *World Development, 57*, 114–126. https://doi.org/10.1016/j.worlddev.2013.12.005
10. Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research, 141*(1), 61–94. https://doi.org/10.1007/s11205-017-1832-9

11. Irikefe, P. O., Thong, Q. Y., Falahat, M., & Samuel, J. (2026). Innovation capability moderates the association between AI readiness and sustainable development in ASEAN. *Discover Sustainability*. Advance online publication. https://doi.org/10.1007/s43621-026-03508-y
12. Kaufmann, D., Kraay, A., & Mastruzzi, M. (2010). *The Worldwide Governance Indicators: Methodology and analytical issues* (Policy Research Working Paper No. 5430). World Bank. https://doi.org/10.1596/1813-9450-5430
13. Köseoglu, M. A., Khaki, A., & Arici, H. E. (2026). AI readiness and sustainable development: A systems perspective on health, education, innovation, and climate action. *Business Strategy & Development, 9*(1), Article e70315. https://doi.org/10.1002/bsd2.70315
14. Kurtz, M. J., & Schrank, A. (2007). Growth and governance: Models, measures, and mechanisms. *The Journal of Politics, 69*(2), 538–554. https://doi.org/10.1111/j.1468-2508.2007.00549.x
15. Liu, Y., Song, J., Zhou, B., & Liu, J. (2025). Artificial intelligence applications and corporate ESG performance. *International Review of Economics & Finance, 104*, Article 104559. https://doi.org/10.1016/j.iref.2025.104559
16. Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity-consistent standard errors in the linear regression model. *The American Statistician, 54*(3), 217–224. https://doi.org/10.1080/00031305.2000.10474549
17. Mahmood, G., Anum, R., & Munir, S. (2026). Role of artificial intelligence and digital infrastructure in enhancing innovation performance of manufacturing sector in emerging economies. *Research Consortium Archive, 4*(1), 433–449.
18. Malik, A., & Sah, A. N. (2024). Can stronger governance and institutional quality drive growth through inward foreign direct investments in BRICS nations? *South African Journal of Economic and Management Sciences, 27*(1), Article a5785. https://doi.org/10.4102/sajems.v27i1.5785
19. Mansour, M., Al Zobi, M., & Alomair, M. (2026). Artificial intelligence, ESG governance, and green innovation efficiency in emerging economies. *Economies, 14*(1), Article 11. https://doi.org/10.3390/economies14010011
20. Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly, 36*(4), Article 101385. https://doi.org/10.1016/j.giq.2019.06.002
21. Mudey, M. H., Arshad, R., & Abdullahi, U. (2026). E-government as anti-corruption tool: Insights from a systematic literature review. *Cogent Social Sciences*. Advance online publication. https://doi.org/10.1080/23311886.2026.2648115
22. North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.
23. Ouakil, H., Lechheb, H., El Arfaoui, M., & Salhi, Z. (2026). AI readiness and public governance in Africa: A system GMM and spatial regression analysis. *Digital Policy, Regulation and Governance*. Advance online publication. https://doi.org/10.1108/DPRG-11-2025-0408
24. Oxford Insights. (2024). *Government AI Readiness Index 2024*. Oxford Insights.
25. Patra, S. K., Dixit, T., & Jangid, K. J. (2026). Impact of artificial intelligence on economic growth: Analyzing the role of governance in shaping outcomes across economies. *Economics of Governance, 27*(1). https://doi.org/10.1007/s10101-026-00361-7
26. Rodrik, D., Subramanian, A., & Trebbi, F. (2004). Institutions rule: The primacy of institutions over geography and integration in economic development. *Journal of Economic Growth, 9*(2), 131–165. https://doi.org/10.1023/B:JOEG.0000031425.72248.85
27. Saba, C. S., & Ngepah, N. (2024). The impact of artificial intelligence (AI) on employment and economic growth in BRICS: Does the moderating role of governance matter? *Research in Globalization, 8*, Article 100213. https://doi.org/10.1016/j.resglo.2024.100213
28. Seiam, D. A. (2024). Examining the global influence of e-governance on corruption: A panel data analysis. *Future Business Journal, 10*(1), Article 29. https://doi.org/10.1186/s43093-024-00319-3
29. Sitnicka, S., Mursalov, M., Mammadov, H., Babaiev, D., & Zhou, Y. (2025). Ethics, institutions, infrastructure, and governance in AI national-level readiness: A hidden driver of banking transformation. *Business Ethics and Leadership, 9*(3), 290–304. https://doi.org/10.61093/bel.9(3).290-304.2025

30. Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly, 36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008
31. Wang, Y., Wang, Y., & Yang, P. (2025). Does artificial intelligence impact corporate ESG performance? Evidence from a quasi-natural experiment in China. *Energy Economics, 151*, Article 108963. https://doi.org/10.1016/j.eneco.2025.108963
32. Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector: Applications and challenges. *International Journal of Public Administration, 42*(7), 596–615. https://doi.org/10.1080/01900692.2018.1498103
33. Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.
34. World Bank. (2024a). *World Bank country and lending groups*. World Bank.
35. World Bank. (2024b). *World Development Indicators*. World Bank.
36. World Bank. (2024c). *Worldwide Governance Indicators*. World Bank.
37. Xie, H., & Wu, F. (2025). Artificial intelligence technology and corporate ESG performance: Empirical evidence from Chinese-listed firms. *Sustainability, 17*(2), Article 420. https://doi.org/10.3390/su17020420
38. Yao, M., Chen, W., Mallek, S., & Shahzadi, I. (2026). Regulatory governance and AI innovation quality: A cross-country evaluation of technology, institutions, and ESG outcomes. *Technological Forecasting and Social Change, 230*, Article 124733. https://doi.org/10.1016/j.techfore.2026.124733
39. Zhao, Y., & Du, Z. (2025). Digital governance, anti-corruption and political stability: An empirical study using cross-national panel data. *PLOS ONE, 20*(12), Article e0338630. https://doi.org/10.1371/journal.pone.0338630
40. Zheng, H., Wu, J., Li, R., & Song, Y. (2025). The role of artificial intelligence in renewable energy development: Insights from less developed economies. *Energy Economics, 146*, Article 108551. https://doi.org/10.1016/j.eneco.2025.108551

6. Appendices:

Appendix Fig A1: CAIRI Trends and First-Difference Evidence



Note: Panel A shows CAIRI trends by income group; Panel B plots changes in CAIRI against changes in Rule of Law, 2020–2024.