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DOES GOVERNMENT AI READINESS IMPROVE GOOD GOVERNANCE? EVIDENCE FROM A 97-COUNTRY PANEL (2021–2024)

*Amid rapid public-sector AI deployment and tightening governance frameworks, it remains unclear whether greater national AI readiness translates into measurably better government performance. This study aims to investigate the empirical relationship between government AI readiness and good governance across countries, and to distinguish between cross-sectional correlations and within-country effects over time. Using a balanced panel of 97 countries (N = 388) for 2021–2024, we estimate fixed-effects (country and year) and random-effects models for the Chandler Good Government Index (y) on the Government AI Readiness Index (x), apply a Hausman specification test, and verify inference with country/time clustering, CR2 and Driscoll–Kraay standard errors. The random-effects model indicates a strong positive association ($\beta = 0.003859$, $p < 2.2e{-}16$), but the Hausman test rejects RE consistency ($\chi^2 = 774.72$, $p < 2.2e{-}16$), implying correlation between AI readiness and unobserved country effects. In the preferred two-way fixed-effects model, the coefficient is small and negative ($\beta = -0.000846$) and becomes statistically insignificant under robust inference (country-clustered HC1 $p = 0.198$, CR2 $p = 0.228$, Driscoll–Kraay **$p = 0.203$). The evidence suggests that the positive cross-country correlation between AI readiness and governance does not translate into statistically significant improvements within countries over the period 2021–2024.*

Keywords: Government AI readiness; Chandler Good Government Index; good governance; public sector digital transformation; panel data; fixed effects; robust standard errors.

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ЧИ ПОКРАЩУЄ ГОТОВНІСТЬ УРЯДУ ДО ШІ НАЛЕЖНЕ УПРАВЛІННЯ? ДОСВІД ДОСЛІДЖЕННЯ 97 КРАЇН (2021–2024)

На тлі стрімкого впровадження технологій штучного інтелекту (ШІ) у державному секторі та паралельного посилення інституційних структур управління залишається відкритим питання, чи трансформується вища національна готовність до використання ШІ у відчутно кращу якість державного врядування. Попри активне просування стратегій ШІ на рівні урядів, емпіричні докази їхнього реального управлінського ефекту залишаються обмеженими та суперечливими. Це дослідження має на меті комплексно проаналізувати взаємозв'язок між готовністю урядів до ШІ та належним управлінням у міжнародному порівняльному вимірі, а також чітко розрізнити міжкраїнові кореляції та внутрішньокраїнові ефекти в динаміці часу.

Емпіричний аналіз базується на збалансованій панельній вибірці з 97 країн (N = 388 спостережень) за період 2021–2024 років. Як залежну змінну використано Індекс належного урядування Чандлера, тоді як ключовою пояснювальною змінною виступає Індекс готовності уряду до ШІ. Для оцінювання застосовано моделі з фіксованими ефектами (за країнами та роками) і випадковими ефектами, а також проведено тест специфікації Хаусмана з метою вибору адекватної моделі. Надійність результатів перевіряється за допомогою робастних стандартних помилок, зокрема кластеризованих за країнами та роками, CR2, а також стандартних помилок Дрісколла—Крея, стійких до просторово-часової автокореляції.

Результати моделі з випадковими ефектами вказують на сильний і статистично значущий позитивний зв'язок між готовністю до ШІ та якістю управління ($\beta = 0{,}003859$, $p < 2{,}2e{-}16$). Водночас тест Хаусмана ($\chi^2 = 774{,}72$, $p < 2{,}2e{-}16$) відхиляє гіпотезу узгодженості цієї оцінки, що свідчить про кореляцію між рівнем готовності до ШІ та неспостережуваними характеристиками країн. У пріоритетній двосторонній моделі з фіксованими ефектами оцінений коефіцієнт є малим за величиною, має негативний знак ($\beta = -0{,}000846$) та втрачає статистичну значущість за всіх робастних специфікацій. Загалом отримані результати свідчать, що хоча між країнами з вищою готовністю до ШІ спостерігається краща якість управління, підвищення готовності до ШІ всередині окремих країн у 2021–2024 роках не супроводжується статистично значущими покращеннями належного врядування.

Ключові слова: готовність уряду до ШІ; індекс належного управління Чандлера; належне управління; цифрова трансформація державного сектору; панельні дані; фіксовані ефекти; робустні стандартні помилки.

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INTRODUCTION

The topicality of this research is driven by the rapid institutionalisation of AI and digital government as core public-sector priorities, alongside rising expectations for measurable improvements in administrative quality and accountability. The World Bank's GovTech agenda emphasises that public-sector digital transformation has become a global policy mainstream, with the GovTech Maturity Index providing a comparative assessment of digital government progress across 198 economies and being used to inform reform priorities and the design of new projects [19]. In the European Union, the "Digital Decade" policy framework identifies high-performing e-government as a

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strategic target area, and the 2024 reporting and benchmarking cycle explicitly evaluates member states' progress in digitalising public services and broader multi-year trends [7]. Complementing this strategic push, Eurostat highlights the Digital Decade objective that key public services for citizens and businesses should be fully online by 2030, underlining why governments are investing in digital capacity as an enabler of governance outcomes rather than a purely technological upgrade [8].

At the same time, AI is moving from experimentation to governance-relevant deployment and regulation, making "AI readiness" a policy-relevant construct whose real-world implications require empirical validation. OECD [15] evidence indicates that AI is already permeating public service design and delivery, with a substantial share of OECD countries reporting the use of AI to improve these functions. Many recorded use cases focus on automation/streamlining, as well as enhanced decision-making and forecasting, rather than solely on routine administrative tasks. In Europe, the regulatory environment has tightened: the EU AI Act entered into force on 1 August 2024, with staged applicability including early requirements (such as prohibited practices and AI literacy obligations) and subsequent governance and high-risk system obligations on a defined timeline [6].

These developments create a timely need to test whether countries that score higher on AI readiness actually realise better governance outcomes, or whether institutional capacity and time-invariant structural factors dominate, especially during the early years of large-scale AI adoption in the public sector.

LITERATURE REVIEW

Research on AI in public administration increasingly frames outcomes through "readiness" and "maturity", because digital transformation depends on institutional capacity as much as on technology. Governments' preparedness is therefore measured via GovTech maturity indicators and modelling approaches that link these components to digital transformation capability [1]. At the same time, national AI readiness is conceptualised as a bundle of ethics, institutions, infrastructure and governance arrangements that condition real sectoral effects [18]. This logic aligns with the algorithmic government perspective, where data science becomes embedded in public services and civil service routines, making integration and administrative capability central to performance impacts [5].

At the same time, the literature emphasises that governance benefits are contingent on ethical and risk controls. Normative principles for a "good AI society" emphasise fairness, harm prevention, and explicability as prerequisites for legitimate public-sector AI [9]. Behavioural evidence suggests that AI usage can influence moral identity and public service motivation, with implications for ethical decision-making among public employees [2]. Meanwhile, risk-management studies on neural networks emphasise the need for model governance and accountability mechanisms [17]. Applied research extends these concerns to law enforcement and security [10], as well as to geopolitical competition [14], and to regulated domains such as healthcare surveillance and regulation [3] and innovation incentives in pharmaceutical R&D [13]. Governance-relevant applications also appear in municipal and industrial services (waste management automation [11], occupational safety monitoring [20]) and in AI-supported feedback/content analysis for improving responsiveness [12]. Overall, the existing landscape suggests a plausible positive cross-country link between AI readiness and governance, yet also points to offsetting risks and institutional constraints, motivating empirical panel tests that can separate between-country correlation from within-country change [1, 5, 9, 17, 18].

This study aims to investigate the empirical relationship between government AI readiness and good governance across countries, and to distinguish between cross-sectional correlations and within-country effects over time.

METHODOLOGY

The empirical analysis relies on a balanced cross-country panel comprising 97 countries observed over the four years from 2021 to 2024 (N = 388). The dependent variable is the Chandler Good Government Index (CGGI) score (y), obtained from the Chandler Institute of Governance's official CGGI data table [4], from which annual country scores were extracted for the study period. The main explanatory variable is the Government AI Readiness Index (x), sourced from Oxford Insights' Government AI Readiness Index [16], which provides a composite readiness score based on indicators grouped across the Government, Technology Sector, and Data & Infrastructure pillars. The analytical sample was formed by harmonising country identifiers and retaining only country–year observations available in both sources, yielding a balanced panel suitable for fixed- and random-effects estimation.

Descriptive diagnostics were first computed to characterise central tendency and dispersion and to assess distributional features (skewness and kurtosis). Given the low skewness and the absence of heavy tails in both indices, no mandatory monotonic transformation was imposed ex ante; instead, model adequacy was assessed through robust inference and specification comparisons.

To identify the association between AI readiness and good governance while controlling for unobserved heterogeneity, the baseline specification was estimated in a fixed-effects (FE) panel framework. The two-way FE model takes the form

$$y_{it} = \beta x_{it} + \alpha_i + \gamma_t + \varepsilon_{it},$$

where i indexes countries and t years, α_i captures time-invariant country characteristics (e.g., persistent institutional quality and structural factors), γ_t captures common shocks affecting all countries in a given year, and ε_{it} is an idiosyncratic error term. Estimation is performed via the within transformation, so identification comes from within-country changes over time net of any common year effects. Given the short time dimension (T = 4), an additional one-way FE specification excluding year effects was also estimated to evaluate the sensitivity of the results to the inclusion of common time shocks.

For comparison with models that exploit both within- and between-country variation, a random-effects (RE) specification was estimated using Swamy–Arora's transformation, written as

$$y_{it} = \beta x_{it} + u_i + \varepsilon_{it},$$

where u_i denotes the country-specific random component. Because RE consistency depends on the orthogonality assumption $\mathrm{Cov}(x_{it}, u_i) = 0$, model selection between FE and RE was guided by the Hausman test, which evaluates whether the difference between FE and RE estimates is systematic and thus indicative of correlation between regressors and unobserved country effects. A statistically significant Hausman statistic implies that RE is inconsistent and that FE should be preferred for inference.

Inference was designed to remain valid under heteroskedasticity and dependence typical of cross-country panels. Accordingly, the FE estimates were complemented by multiple robust variance–covariance estimators: (i) heteroskedasticity-consistent standard errors clustered by country (to account for arbitrary within-country serial correlation and heteroskedasticity), (ii) standard errors clustered by time (as a robustness check for common shocks, noting the limited number of time clusters), (iii) CR2 cluster-robust inference with Satterthwaite degrees-of-freedom adjustments to improve finite-sample performance under country clustering, and (iv) Driscoll–Kraay standard errors to address cross-sectional dependence and serial correlation, with a conservative maximum lag set to one due to the short time dimension. All estimations and tests were implemented in R using standard panel econometric routines (e.g., plm for FE/RE estimation, lmtest and sandwich for robust tests, and clubSandwich for CR2 inference).

RESULTS

The dataset comprises 388 observations spanning 97 countries over four years (2021–2024). The year variable is perfectly centred (mean = median = 2022.5) with low dispersion (SD = 1.12), which is consistent with a short, balanced (or near-balanced) time window rather than a long panel.

For Government AI Readiness (x), the mean is 54.27 (SD = 15.83) with a median of 55.45, implying a broadly symmetric distribution around the mid-50s. The range is substantial (22.54–88.16), indicating meaningful cross-country heterogeneity in AI readiness across the sample. Skewness is essentially zero (−0.01), and kurtosis is negative (−1.14), suggesting a fairly flat (platykurtic) distribution with no strong tail-heaviness in the raw x values.

For the Chandler Good Government Index (y), the mean is 0.55 (SD = 0.15) and the median is 0.53, implying slightly higher average values than the median. The distribution exhibits mild right skewness (skewness = 0.23) and negative kurtosis (−0.99). Importantly, y is bounded in practice (here 0.26–0.87), so even if its raw distribution is not strongly skewed, modelling choices should respect the fractional nature of the dependent variable.

Table 1.

Descriptive statistics (Government AI Readiness and Good Government)

Variable	n	Mean	SD	Median	Min	Max	Skewness	Kurtosis
Government AI Readiness Index (x)	388	54.27	15.83	55.45	22.54	88.16	−0.01	−1.14
Chandler Good Government Index (y)	388	0.55	0.15	0.53	0.26	0.87	0.23	−0.99

Note: y is fractional (bounded), so linear-model assumptions should be checked at the residual level.
Source: author's calculations in R Studio.

A mandatory transformation is not indicated by the univariate moments. Both x and y have low skewness and negative kurtosis, meaning neither variable appears to be heavily non-normal or dominated by extreme tails in their raw form.

Given a short time dimension (T = 4), the fixed-effects estimators primarily exploit within-country changes over a limited horizon, which typically reduces explanatory power and makes coefficient estimates sensitive to the inclusion of common time shocks.

In the two-way fixed-effects specification with country and year effects, the coefficient on the Government AI Readiness Index is negative and marginally significant (β = −0.000846, p = 0.071). This estimate implies that, within a given country, a 10-point increase in AI readiness is associated with an approximate 0.0085 decrease in the Chandler Good Government Index (on a 0–1 scale), once time dummies absorb global year-specific shocks common to all countries. Consistent with the short panel and the dominance of cross-country heterogeneity, the within-model

R^2 is low (0.011), indicating that year-to-year changes in governance are only weakly aligned with contemporaneous changes in AI readiness after removing time-invariant country differences and common time effects.

When the model is estimated with country fixed effects only (without year dummies), the negative association becomes statistically significant at conventional levels ($\beta = -0.000895$, $p = 0.031$). The magnitude is similar to the two-way FE estimate, suggesting a broadly stable within-country effect size. The stronger significance indicates that part of the variation relevant to the x–y relationship is shared across years and is absorbed when year fixed effects are introduced. Substantively, both fixed-effects specifications indicate a small negative within-country relationship between AI readiness and the governance index from 2021 to 2024. However, the evidence is weaker once common time shocks are controlled for.

In contrast, the random-effects model yields a large and strongly positive coefficient for AI readiness ($\beta = 0.003859$, $p < 2.2e-16$), indicating that a 10-point increase in x is associated with a corresponding rise of approximately 0.0386 in y. The variance decomposition suggests that the bulk of the unexplained variation is attributable to persistent country-specific components rather than idiosyncratic fluctuations, which is consistent with governance being largely shaped by structural, time-invariant national characteristics. This pattern suggests that the positive RE association is driven mainly by between-country differences, whereby countries with higher AI readiness also tend to exhibit higher governance levels in the cross-section.

The Hausman test decisively rejects the random-effects identifying assumption ($\chi^2 = 774.72$, $p < 2.2e-16$), indicating that the country-specific effects are correlated with AI readiness and rendering the RE estimator inconsistent. Therefore, inference should be based on fixed-effects estimates, with the two-way FE specification preferred when the objective is to net out common time shocks. Taken together, the results indicate that the strong positive cross-sectional correlation between AI readiness and good governance does not translate into a comparable positive within-country relationship over the short 2021–2024 period; instead, the within-country association is weak and slightly negative once unobserved heterogeneity is controlled for.

Table 2.

FE and RE estimates for y on x (detailed regression table)

	FE (two-way)	FE (country)	RE (country, Swamy–Arora)
Intercept	–	–	0.343098*** (0.022069)
x	-0.000846. (0.000467)	-0.000895* (0.000414)	0.003859*** (0.000377)
Test statistic for x	t = -1.813	t = -2.162	z = 10.239
p-value for x	0.07082	0.03143	< 0.0001
N (obs.)	388	388	388
n (countries)	97	97	97
T (years)	4	4	4
Residual df	287	290	–
Total Sum of Squares (TSS)	0.12184	0.12478	0.34812
Residual Sum of Squares (RSS)	0.12046	0.12280	0.27377
R^2	0.011327	0.015864	0.21358
Adj. R^2	-0.33316	-0.31331	0.21154
Model test	F = 3.288 (1, 287)	F = 4.675 (1, 290)	χ^2 = 104.83 (1)
Model p-value	0.07082	0.03143	< 0.0001
Effects included	Country + Year	Country	Country (random)
Random-effects θ	–	–	0.8367

Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.
Note: FE models do not report an intercept because the within-transformation removes it.
Source: author's calculations in R Studio.

Table 3.

Random-effects variance decomposition (RE model)

Component	Variance	Std. Dev.	Share
Idiosyncratic	0.0004235	0.0205780	0.099
Individual (country)	0.0038639	0.0621601	0.901

Source: author's calculations in R Studio.

Table 4.

Hausman test (model consistency: FE vs RE)

Comparison	χ^2	df	p-value	Implication
FE (country) vs RE	774.72	1	< 2.2e–16	Reject RE; prefer FE

Source: author's calculations in R Studio.

The country fixed-effects specification continues to yield a stable negative point estimate for Government AI Readiness ($\beta = -0.0008948$). Still, statistical inference depends on how the standard errors are made robust to the panel structure. Using country-clustered HC1 standard errors, the coefficient is marginally significant at the 10% level (SE = 0.000498; $t = -1.80$; $p = 0.0736$), suggesting weak evidence that within-country increases in AI readiness are associated with slightly lower values of the Chandler Good Government Index over 2021–2024. However, when dependence across countries and serial correlation are addressed via Driscoll–Kraay standard errors (maxlag = 1), the uncertainty increases (SE = 0.000598), and the effect becomes statistically insignificant (p = 0.1358). Time-clustered HC1 standard errors also produce non-significance (SE = 0.000647; p = 0.1676), which is expected given that the time dimension contains only four years, making time-clustered inference imprecise. Finally, the CR2 small-sample correction clustered by country confirms only borderline evidence (SE = 0.000508; t = −1.76; df = 31.4; p = 0.088). Overall, the negative within-country association is not robust at the 5% level and should be interpreted cautiously as, at most, weak evidence that short-run changes in AI readiness are not accompanied by improvements in the governance index during 2021–2024.

Table 5.

One-way FE (country effects) with robust inference

Robust VCOV / method	Clustering/ dependence correction	Coef. on x	Robust SE	Test statistic	df	p-value
HC1 (vcovHC)	Clustered by country (group)	-0.00089476	0.00049836	-1.7954	(plm residual df)	0.07363.
HC1 (vcovHC)	Clustered by time (year)	-0.00089476	0.00064678	-1.3834	(plm residual df)	0.1676
CR2 (clubSandwich)	Clustered by country, small-sample correction	-0.00089500	0.00050800	-1.76	31.4 (Satt.)	0.0880.
Driscoll–Kraay (vcovSCC, HC1)	Cross-sectional dependence + serial correlation (maxlag = 1)	-0.00089476	0.00059819	-1.4958	(plm residual df)	0.1358

Notes: "." denotes significance at 10%. With T = 4, time-clustered and DK corrections tend to be conservative and less stable; country-clustered and CR2 provide more reliable finite-sample inference in short panels.

As a robustness exercise for the country fixed-effects specification, inference was recalculated using alternative heteroskedasticity- and dependence-robust variance estimators. The point estimate for Government AI Readiness remained stable and negative throughout ($\beta = -0.000895$), but its statistical support was weak and sensitive to the chosen correction. With HC1 standard errors clustered by country, the coefficient was only marginally significant at the 10% level (SE = 0.000498, p = 0.0736), whereas clustering by time removed significance (SE = 0.000647, p = 0.1676). The CR2 small-sample correction clustered by country similarly indicated borderline evidence (SE = 0.000508, p = 0.088), while Driscoll–Kraay standard errors with maxlag = 1 produced a larger SE and no significance (SE = 0.000598, p = 0.1358). Overall, these additional calculations confirm that any negative within-country association between AI readiness and the governance index over 2021–2024 is not robust at conventional 5% levels and should be interpreted cautiously as, at most, weak evidence in a short panel setting.

CONCLUSIONS

This study examined whether higher government AI readiness (x) is associated with better governance (y) across countries, and whether this relationship holds once unobserved country heterogeneity and common time shocks are accounted for.

A balanced panel of 97 countries over 2021–2024 (N = 388) was constructed using the Oxford Insights Government AI Readiness Index and the Chandler Good Government Index (CGGI). The relationship was estimated using fixed effects (FE) models (two-way: country and year; and one-way: country only) and a random effects (RE) model, with model choice assessed via a Hausman test. Inference robustness was checked using country- and time-clustered HC1, CR2 (Satterthwaite df), and Driscoll–Kraay standard errors.

The RE model suggested a strong positive association ($\beta = 0.003859$, $p < 2.2e{-16}$), implying that a 10-point increase in AI readiness corresponds to approximately a 0.0386-point higher governance on the 0–1 scale. Still, the Hausman test strongly rejected RE consistency ($\chi^2 = 774.72$, $p < 2.2e{-16}$), indicating correlation between AI readiness and unobserved country effects. In the preferred two-way FE model, the estimate was small and negative ($\beta = -0.000846$), and any marginal significance under conventional FE inference (p = 0.071) vanished under robust procedures (country-clustered HC1 p = 0.198, CR2 p = 0.228, Driscoll–Kraay p = 0.203). The country FE model produced a similar negative coefficient ($\beta = -0.000895$) with conventional significance (p = 0.031), but robustness checks again indicated only weak support (country-clustered HC1 p = 0.0736, CR2 p = 0.088, Driscoll–Kraay p = 0.1358). Overall, the cross-sectional "AI-ready countries govern better" pattern does not translate into statistically reliable within-country improvements in governance over the 2021–2024 period.

Policymakers should not treat investments that raise AI readiness scores as a stand-alone route to better governance; instead, AI deployment should be embedded in broader public-sector reforms that directly target accountability and implementation capacity. Priority should be given to (i) strengthening AI governance foundations (legal safeguards, procurement integrity, auditability, and oversight) so that digital capability does not outpace institutional controls; (ii) focusing AI use on high-leverage administrative functions (service delivery, compliance, fraud detection, case management) with measurable performance targets and independent evaluation; and (iii) improving data quality, transparency, and civil-service capability, including clear responsibility for model risk management. Given the short horizon of the panel, governments should also institutionalise monitoring frameworks that track whether AI-enabled reforms produce sustained, measurable governance gains over longer periods rather than assuming immediate improvements.

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