“E-government development: Artificial intelligence vibrancy and readiness as drivers of digital public administration”

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E-GOVERNMENT DEVELOPMENT: ARTIFICIAL INTELLIGENCE VIBRANCY AND READINESS AS DRIVERS OF DIGITAL PUBLIC ADMINISTRATION

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Abstract

Artificial intelligence is shaping digital governance, with global organizations emphasizing its opportunities and risks for public administration. The study aims to assess whether advancements in AI, measured by the AI Vibrancy Score (AIVS) and the Government AI Readiness Index (GAIRI), drive improvements in the E-Government Development Index (EGDI). Using panel data methods, the analysis draws on data from 36 countries for 2018–2022 (AIVS–EGDI) and 170 countries for 2020–2024 (GAIRI–EGDI), due to differing data availability and indicator coverage periods, applying fixed effects, random effects, and Mundlak specifications, combined with robust inference techniques. The results demonstrate that within-country improvements in AI readiness are positively and robustly associated with higher levels of e-government development, with the FE estimate for the Government AI Readiness Index equal to 0.17 ($p < 0.001$). RE models reveal stronger cross-country correlations, with coefficients of 2.55 ($p < 0.001$) for the AI Vibrancy Score and 0.35 ($p < 0.001$) for AI readiness. However, Mundlak (correlated RE) specifications indicate that the between-country components are statistically insignificant. Yet, the within-country effects remain significant, suggesting that dynamic national reforms and policy-driven progress outweigh inherited structural advantages. Time effects are pronounced, with positive and significant shifts in 2020 (+7.02) and 2022 (+8.10) relative to the baseline year, reflecting the acceleration of digital public administration during the post-pandemic period. Country-specific effects exhibit substantial heterogeneity, ranging from strongly positive deviations (e.g., Denmark, Estonia, Korea) to persistently negative ones (e.g., India, South Africa), underscoring the uneven national trajectories. Robustness checks using clustered standard errors confirm the stability of all key coefficients.

Keywords government AI readiness, AI vibrancy, e-government development, digital public administration, government services

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INTRODUCTION

AI is now a first-order macro shock with direct implications for governments, employers, regulators, and service providers. The IMF estimates that roughly 40% of jobs worldwide are exposed to AI, with potentially significant productivity gains alongside distributional risks. This outlook heightens pressure on the public sector to modernize how it designs and delivers services. Recent IMF analysis highlights that aggregate productivity effects could be positive, but the transition will be uneven and policy-dependent (Georgieva, 2024). In parallel, the ILO's latest work on generative AI reveals wide cross-country and cross-occupational heterogeneity in exposure, with many tasks likely to be augmented rather than fully automated, again placing public administration at the center of skills, regulation, and inclusion agendas

(Gmyrek et al., 2025). Together, these assessments sharpen the need to understand whether countries that invest in AI capabilities are also those advancing most in digital government.

On the government side, digital transformation is both a political mandate and a measured performance objective. The EU's Digital Decade (European Commission, 2023b) sets concrete targets for 2030 on digital public services and interoperable identities, while the eGovernment Benchmark 2023 documents uneven progress across European states, highlighting persistent gaps in user-centricity, transparency, and cross-border availability (European Commission, 2023a). Globally, the World Bank's GovTech Maturity Index 2022 reports improvement in core platforms and citizen-facing services, yet also identifies capability gaps (Dener, 2022); its broader Digital Progress and Trends work stresses that the "digital divide" increasingly mirrors a development divide (World Bank, 2024). These institutional signals make it timely to test, with comparative data, whether AI readiness translates into measurable gains in e-government development.

Policy frameworks for AI governance are also evolving quickly but unevenly. The World Bank Group (2024) finds that countries are experimenting with divergent regulatory and institutional models for AI, raising the stakes for evidence on which capabilities matter most for public-sector outcomes. By coupling internationally recognized indicators of AI vibrancy/readiness with the UN's e-government metrics in a panel setting, this study addresses a live empirical question with direct operational relevance: are governments that build AI capacity the same ones delivering better, more accessible digital services? The answer can inform the sequencing of reforms (skills, data, and platforms) and the design of safeguards to ensure that the benefits of AI-enabled administration are inclusive and accountable.

1. LITERATURE REVIEW AND HYPOTHESES

E-government development has increasingly been conceptualized as a multidimensional transformation in which digital infrastructures, administrative capacity, and strategic decision-making jointly determine how effectively public services are delivered and governed. Evidence from management and organizational research suggests that digitalization enhances decision quality and strategic control when it is embedded in coherent governance routines, rather than being treated as a purely technical upgrade (Bondar et al., 2024; El Massaoudi et al., 2025). At the macro level, digitalization is also positioned as a competitiveness-enhancing force that shapes national development pathways and resilience, implying that e-government performance is intertwined with broader trajectories of digital economy maturity (Jarzębowski et al., 2024; Kusairi et al., 2023; Stender et al., 2024; Kozhushko, 2023; Masyk et al., 2023).

Artificial intelligence has become a central accelerator of this agenda, as public administrations seek to automate processes, enhance analytical capacity, and personalize service delivery. The public governance literature highlights that generative AI, in particular, expands the scope of digital public administration by enabling new forms of citizen interaction, rapid content generation, and decision support, while simultaneously raising questions about accountability and institutional preparedness (Androniceanu, 2024; Murko et al., 2024; Kildei et al., 2025). This has stimulated a shift from considering "digital government" as the adoption of ICT systems toward examining the conditions under which AI becomes a productive capability for the state, captured empirically through readiness- and vibrancy-type constructs that proxy the maturity of AI ecosystems and their capacity to diffuse into public service provision (Iuga & Socol, 2024).

A consistent message across adjacent domains is that AI-driven performance gains depend on complementary capabilities, including skills, training, and organizational change management. The importance of building human capital for AI adoption is emphasized in sectoral evidence where AI training is linked to successful digital transformation outcomes and strategic objectives, underscoring the role of learning in translating technology into measurable organizational improvement (Abou-

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Moghli, 2026; Lazaroiu & Rogalska, 2023; Kytsak & Ovsiannykov, 2025; Panasiuk & Kravchuk, 2025; Roieva et al., 2023). Similar complementarities are also evident in knowledge-management settings, where smart technologies enhance performance only when they are integrated into institutional routines and information governance (Mahmoud et al., 2025). These insights are directly relevant to e-government because EGDI improvements typically require organizational redesign, not merely platform deployment. Broader technology foresight work additionally suggests that AI is increasingly embedded in converging digital ecosystems (e.g., digital twins, XR, IoT/robotics), indicating that e-government development may increasingly depend on the ability of administrations to govern and integrate complex cyber–physical systems rather than isolated digital platforms (Lazaroiu et al., 2024; Salnikova et al., 2019).

The finance and service innovation literature further clarifies how AI readiness can operate as a systemic enabler by strengthening data capabilities, service integration, and value co-creation. Empirical work links AI and big data capabilities to improved fintech service provision through value co-creation mechanisms, while other studies emphasize that culturally aligned adoption frameworks can shape inclusion and diffusion in financial ecosystems (Khaddam & Alhanatleh, 2024; Othman, 2025; Polishchuk, 2023). Parallel evidence from digital finance and InsurTech suggests that integration across platforms is a practical bottleneck and that institutional coordination is crucial for realizing the benefits of digital transformation (Kozhushko, 2023; Khrais, 2025). These mechanisms resemble the coordination challenges of e-government, where cross-agency interoperability and trust frameworks determine whether AI capabilities lead to improvements in citizen-facing services.

At the same time, the governance implications of AI adoption underscore that ethical risks, bias, and legitimacy deficits can undermine the gains of digital public administration. Research on unethical AI awareness and mitigation reveals that risk governance and safeguards are crucial for the responsible deployment of AI, suggesting that AI readiness should be understood as encompassing both ethical and regulatory capacity, as well as technical sophistication (Höller et al., 2023; Mura & Stehlíková, 2025; Bashynska, 2025). Evidence from law enforcement applications underscores that automated decision-making can introduce distributive impacts and social justice concerns, particularly when accountability mechanisms are weak (Haley, 2025; Haley & Burrell, 2025). From an e-government perspective, these strands suggest that improvements in EGDI are likely to be more sustainable where AI adoption is aligned with transparency, procedural fairness, and citizen trust.

The security, integrity, and anti-crime literature reinforces the argument that digital governance capacity shapes state effectiveness in high-risk environments, thereby linking e-government development to the broader integrity ecosystem. Digital transformation is associated with strengthened anti-corruption and cyber-fraud systems, indicating that digital public administration can reduce opportunities for illicit behavior when oversight and institutional coordination improve (Yarovenko et al., 2025, 2024b). Related evidence on AI and machine learning in combating illegal financial operations illustrates both the expanding role of AI in governance functions and the strategic adaptation by offenders, which raises the bar for institutional readiness and capacity-building (Lyeonov et al., 2024, 2025). These findings suggest that AI vibrancy without governance maturity may yield uneven gains, underscoring the importance of distinguishing between "capability availability" and "capability use" in explaining EGDI outcomes.

Cross-sectoral research also suggests that AI readiness has spillover effects that can strengthen public value through improved service quality, risk management, and resilience in critical systems. Evidence linking government AI readiness to energy security, and broader work on AI-enabled energy equity and energy security via supply chains, positions AI as a capability that supports complex system management, an increasingly central function of modern public administration (Kuzior et al., 2025; Kirichok et al., 2025; Wang et al., 2025; Ganushchak et al., 2025). Similar logic is evident in studies of supply-chain efficiency and strategic control, where AI enhances coordination and performance when supported by robust governance and data systems (Golubtsov et al., 2025; El Massaoudi et al., 2025). These strands strengthen the expectation that countries with more mature AI ecosystems and readiness frameworks are better positioned to advance e-government development.

Despite these advances, the scientific landscape remains fragmented, with much of the evidence being sector-specific (marketing, fintech, healthcare, energy) or focused on ethical risks, while fewer studies directly quantify how AI ecosystem maturity translates into digital public administration outcomes at the cross-country level (Dabija & Frau, 2025; Pilelienė & Bogoyavlenska, 2025; Kritikos et al., 2025; Kuzior et al., 2024; Ustik et al., 2023; Máté et al., 2024; Schinello, 2025). Furthermore, structural macroeconomic dynamics and resource-dependence contexts can mediate digital transitions, suggesting that country trajectories and institutional baselines should be explicitly modelled rather than assumed away (Bouguerroumi & Belarbi, 2025; Salnikova et al., 2019). This motivates a research design that links AI vibrancy and AI readiness to EGDI through panel-based evidence while controlling for persistent national heterogeneity.

Prior research supports the view that AI can strengthen digital public administration, but only where readiness encompasses human capital, institutional coordination, and ethical safeguards. At the same time, cross-country disparities and sectoral fragmentation leave open the question of whether AI vibrancy and readiness operate primarily through within-country improvements or through persistent structural advantages. These gaps provide a clear rationale for empirically testing AI vibrancy and readiness as drivers of e-government development within a panel framework and for explicitly accounting for country-specific and time-specific effects.

The aim of this study is to assess whether advancements in artificial intelligence contribute to the digitalization of public administration. More specifically, the analysis examines the impact of the AI Vibrancy Score and the Government AI Readiness Index on the E-Government Development Index across a diverse set of countries. By applying panel data methods, the study distinguishes between within-country dynamics and cross-country disparities while testing the robustness of results under alternative model specifications and inference strategies.

To achieve this aim, the following research hypotheses are formulated:

H1: (Within-country effect): Improvements in AI readiness within a country over time are positively associated with advancements in e-government development.

H2: (Between-country effect): Countries with persistently higher levels of AI readiness demonstrate higher levels of e-government development than countries with lower readiness.

H3: (Robustness): The positive relationship between AI readiness and e-government development remains statistically significant after correcting panel-specific econometric issues such as heteroskedasticity, serial correlation, and cross-sectional dependence.

2. METHODOLOGY

First, the relationship between AI development and the digitalization of public administration was investigated by modelling the effect of the AI Vibrancy Score (AIVS) on the E-Government Development Index (EGDI). The analysis is based on a balanced panel dataset covering 36 countries over three time points: 2018, 2020, and 2022, yielding 108 observations. The limited temporal span reflects the availability of the underlying data. The United Nations Department of Economic and Social Affairs (UNDESA) provides EGDI values only through its E-Government Surveys, which are conducted biennially. At the same time, the Stanford University AI Vibrancy Index has been available since 2017, enabling its use from the 2018 reference year onwards.

The country sample is restricted to those included in the Stanford Global AI Vibrancy Tool – AI Index, for which corresponding EGDI data were available. The final dataset consists of 36 countries (Appendix A).

The AIVS (independent variable, x) was obtained from Stanford University's Global AI Vibrancy

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Tool – AI Index (Stanford University, n.d.), aggregating indicators on AI research, development, and adoption. The EGDI (dependent variable, y) was retrieved from the United Nations E-Government Knowledgebase (United Nations, n.d.), which measures the scope and quality of online services, telecommunication infrastructure, and human capital.

The empirical strategy proceeds in three stages. First, descriptive statistics and normality tests were performed to characterize the data. Given that both variables exhibited significant departure from normality, appropriate transformations were applied: the AIVS was normalized using the Box–Cox transformation, while the EGDI was corrected using the Yeo–Johnson transformation. Second, panel models were estimated, including fixed effects (FE), random effects (RE), and correlated random effects (Mundlak specification). The Hausman test guided model choice between FE and RE, while diagnostic tests (Breusch–Pagan LM, Breusch–Godfrey/Wooldridge, Pesaran CD, and Breusch–Pagan heteroskedasticity) were employed to assess the validity of model assumptions. Finally, robust inference techniques (cluster-robust and Driscoll–Kraay standard errors) were applied to mitigate the effects of serial correlation and cross-sectional dependence.

Second, the relationship between AI readiness and e-government development was investigated using the Government AI Readiness Index (GAIRI) as the independent variable (x) and the EGDI as the dependent variable (y). The GAIRI was obtained from Oxford Insights (n.d.), which evaluates the preparedness of governments worldwide to adopt artificial intelligence in public service delivery across various dimensions, including vision, governance, and infrastructure. The EGDI was sourced from the United Nations E-Government Knowledgebase (United Nations, n.d.), which captures the development of e-government services through measures of online service provision, telecommunication infrastructure, and human capital.

The panel dataset comprises 510 observations spanning 170 countries across three time points: 2020, 2022, and 2024. The restricted temporal span is a consequence of data availability: the GAIRI was first introduced in 2019, while the EGDI is provided biennially in the UNDESA E-Government Surveys. The difference in time ranges compared to the previous specification (2018–2022) arises from the use of an alternative AI indicator and expanded country coverage, which necessitate aligning the sample to the years for which both GAIRI and EGDI data are available simultaneously. The country coverage reflects the global scope of the GAIRI, and the final sample is presented in Appendix A.

The empirical strategy mirrored that of the first stage of analysis. Descriptive statistics and normality diagnostics were performed, followed by Box–Cox and Yeo–Johnson transformations to improve the distributional properties. Subsequently, FE, RE, and Mundlak specifications were estimated. The Hausman test guided model selection between FE and RE, while further diagnostic tests (Breusch–Pagan LM, Breusch–Godfrey/Wooldridge, Pesaran CD, and Breusch–Pagan heteroskedasticity) were conducted to evaluate the validity of assumptions. Cluster-robust standard errors were applied to ensure robust inference for serial correlation and cross-sectional dependence.

To explicitly account for unobserved heterogeneity across countries and over time, the analysis incorporated country-specific and time-specific effects within both the fixed-effects and random-effects frameworks with correlation. Country effects were modelled as unobserved, time-invariant components capturing structural institutional, administrative, and socio-economic characteristics that systematically influence e-government development but are not directly observable, such as administrative traditions, governance culture, or long-standing digital infrastructure gaps. In the fixed-effects specification, these effects were eliminated through within-country demeaning, while in the random-effects framework, they were estimated explicitly as country-specific intercepts. To relax the strict exogeneity assumption of standard random-effects models, a Mundlak (correlated random-effects) specification was employed by augmenting the regression with country-level means of the key explanatory variable. This approach decomposes the total effect into within-country (short-term, dynamic) and between-country (long-term, structural) components, allowing for correlation between regressors and unobserved country effects. Time effects were captured through period-specific dummy variables corresponding to the survey years, isolating common global shocks and trends, such as accelerated digitalization during the COVID-19 period or coordinated international AI policy initiatives, that affect all countries simultaneously. The joint inclusion of country effects, time effects, and Mundlak terms ensures a robust identification strategy that disentangles persistent cross-country differences from within-country dynamics over time, thereby strengthening the causal interpretation of the estimated relationships between artificial intelligence vibrancy, AI readiness, and e-government development.

All empirical calculations and econometric estimations were conducted using RStudio with R version 4.4.0. The analysis relied on standard and well-established R packages for panel data modelling, diagnostic testing, and robust inference, ensuring the transparency, replicability, and methodological consistency of the reported results.

3. RESULTS

3.1. AI Vibrancy Score and E-Government Development Index

The descriptive statistics in Table 1 present the dataset's structure and distribution, comprising 108 observations from 36 countries spanning the years 2018 to 2022. The variable country has a mean and median of 18.50, with a standard deviation of 10.44, reflecting the balanced representation of countries across the sample. The year variable confirms the short temporal span of the dataset, with observations centered on 2020 (mean and median 2020), ranging from 2018 to 2022, and exhibiting low variability (SD = 1.64). The negative kurtosis (–1.53) indicates a relatively flat distribution compared to the standard case.

The EGDI shows a mean of 0.85 with a slight standard deviation (0.08), suggesting that most countries are clustered around higher levels of e-government development. The negative skewness (–1.09) indicates that values are concentrated near the upper bound, while the moderately positive kurtosis (1.34) suggests a distribution slightly more peaked than normal.

By contrast, the AIVS demonstrates greater variability, with a mean of 13.22 and a standard deviation of 9.97. The range extends from 0.48 to 47.65, indicating noticeable differences in AI vibrancy across countries. The distribution is positively skewed (1.26), highlighting that a few countries achieve relatively high scores, while most remain below the mean. The kurtosis of 1.72 indicates a somewhat peaked distribution, though without extreme outliers. These features suggest that while AI vibrancy is unevenly spread, it is less dominated by extreme values than in the earlier output, making it more suitable for econometric modelling with limited transformation requirements.

Table 1. Descriptive statistics of the dataset

Variable	EGDI y	AIVS x
N	108	108
Mean	0.85	13.22
SD	0.08	9.97
Median	0.85	11.23
Trimmed	0.85	12.04
MAD	0.07	8.81
Min	0.57	0.48
Max	0.98	47.65
Range	0.41	47.17
Skew	–1.09	1.26
Kurtosis	1.34	1.72
SE	0.01	0.96

The results of the Shapiro–Wilk tests indicate that neither variable follows a normal distribution. For the AIVS (x), the test yielded a W statistic of 0.895 with a p-value < 0.001, providing strong evidence against the null hypothesis of normality. Similarly, the EGDI (y) recorded a W statistic of 0.925 with a p-value < 0.001, again rejecting normality. These outcomes suggest that both variables deviate significantly from a Gaussian distribution, warranting the use of appropriate transformations or robust estimation techniques to account for non-normality.

The Box–Cox transformation of the AIVS, with an estimated λ of approximately 0.34, successfully corrected the distributional asymmetry observed in the original data. The Shapiro–Wilk test applied to the transformed series yielded a *W* sta-

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tistic of 0.991 with a p-value of 0.658, indicating that the null hypothesis of normality cannot be rejected. This confirms that the Box–Cox transformation effectively normalized the distribution of the variable, thereby improving its suitability for econometric analysis and meeting the assumptions of regression models that rely on normally distributed residuals.

The Box–Cox transformation applied to the EGDI improved the distributional properties of the variable, although normality was not fully achieved. The optimal λ suggested by the procedure yielded a Shapiro–Wilk statistic of 0.955 with a p-value of 0.001, which remains below the 5% significance threshold. Thus, the null hypothesis of normality is still rejected, albeit with a higher W value than the untransformed series (W = 0.925). This indicates that while the transformation reduced deviations from normality, the distribution of EGDI retains a degree of negative skewness. The Yeo–Johnson transformation proved more effective than Box–Cox in addressing the non-normality of the EGDI. After transformation, the Shapiro–Wilk test yielded a W statistic of 0.988 and a p-value of 0.478, indicating that the null hypothesis of normality could not be rejected. This marks a substantial improvement compared to both the original series (W = 0.925, p < 0.001) and the Box–Cox transformed version (W = 0.955, p = 0.001). Consequently, the Yeo–Johnson transformation yields a distribution of EGDI that is statistically indistinguishable from normality, enhancing its suitability for econometric modelling where residual normality is an important assumption.

The FE and RE estimations (Table 2) provide contrasting evidence on the relationship between AIVS (Box–Cox transformed) and EGDI (Yeo–Johnson transformed). The country FE specification yielded a small positive coefficient (0.24) for x_bc, but it was statistically insignificant (p = 0.81) and explained virtually none of the within-country variation (R^2 ≈ 0.001). When time effects were also controlled for in the two-way FE model, the coefficient turned negative (–0.41) and remained insignificant (p = 0.57), confirming the absence of a robust within-country effect.

The RE model suggested a strong and statistically significant positive relationship. The estimated coefficient of 2.55 (p < 0.001) suggests that higher AI vibrancy is associated with higher levels of e-government development, both within and between countries. The RE model achieved an R^2 of 0.12, substantially higher than the FE models, and the intercept term was also highly significant.

The Lagrange Multiplier (Breusch–Pagan) test confirmed the presence of significant panel effects (χ^2 = 45.45, p < 0.001), indicating that a random effects specification is preferable to pooled OLS. However, further diagnostics revealed that several key assumptions of the RE model were violated. The Breusch–Godfrey/Wooldridge test detected strong serial correlation in the idiosyncratic errors (χ^2 = 28.87, p < 0.001), while the Pesaran CD test indicated pronounced cross-sectional dependence across units (z = 24.32, p < 0.001). These findings suggest that residuals are not independent over time or across countries. By contrast, the Breusch–Pagan test for heteroskedasticity did not reject the null hypothesis (p = 0.31), implying that error variances are homoscedastic. These diagnostics indicate that although the RE specification is statistically favored over pooled OLS, its standard assumptions are undermined by serial correlation and cross-sectional dependence. This underlines the need for robust inference methods, such as cluster-robust or time-robust standard errors, to obtain consistent estimates and valid statistical inference.

Table 2. Results of FE and RE estimations

Model	Coefficient on x_bc	Std. Error	t/z value	p-value	R² (Adj.)	N	Notes
FE (country)	0.244	1.007	0.242	0.810	–0.506	108	Insignificant
FE (two-way)	–0.409	0.708	–0.578	0.566	–0.543	108	Insignificant
RE (individual)	2.554 ***	0.671	3.805	<0.001	0.112	108	Positive, sig.

Note: Dependent variable = EGDI (Yeo–Johnson transformed). Independent variable = AIVS (Box–Cox transformed). Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

The RE model consistently indicated a statistically significant positive association between AIVS (Box–Cox transformed) and EGDI (Yeo–Johnson transformed) when re-estimated with robust inference (Table 3). With clustering of standard errors at the country level, the coefficient for x_bc was 2.55 ($p < 0.001$), suggesting that countries with higher levels of AI vibrancy are associated with higher levels of e-government development. The result remained robust when clustering by year, with a nearly identical coefficient of 2.55 and strong statistical significance ($p < 0.001$). However, the standard error of the intercept increased, reflecting the limited number of time periods in the panel.

These findings imply that the positive relationship detected by the RE specification is not driven by idiosyncratic heteroskedasticity within countries or standard shocks across years. However, given that the Hausman test rejected the consistency of the RE model in favor of fixed effects, the robustness of these results should be interpreted cautiously. The significance of the RE estimates appears to reflect structural cross-country differences rather than within-country dynamics over time.

The correlated RE (Mundlak) specification enhances the RE model by incorporating the country-level mean of AIVS (xb_mean), offering valuable insights into the relationship between AI vibrancy and e-government development. The coefficient on the within-country variation of x_bc was small (0.24) and statistically insignificant ($p = 0.80$), indicating that short-term changes in AI vibrancy within a given country are not systematically associated with changes in the EGDI. By contrast, the coefficient on the country-level mean of x_bc was positive and highly significant (3.94, $p < 0.01$), even when using cluster-robust standard errors. This suggests that the observed positive association between AI vibrancy and e-government development in the simple RE model is driven primarily by between-country differences, rather than within-country dynamics.

The results support the interpretation that countries with consistently higher levels of AI vibrancy also tend to achieve higher levels of e-government development. However, incremental improvements in AI vibrancy within countries over the short-term horizon do not translate into measurable gains in e-government performance. This finding helps reconcile the divergence between the RE and FE estimates: while the RE model captured the positive cross-sectional association, the FE model, which focuses only on within-country changes, found no significant effect. The Mundlak specification (Table 4), therefore, confirms that the RE assumption of no correlation between individual effects and regressors was violated, and that the genuine relationship is largely cross-sectional in nature.

Table 3. RE estimation with cluster-robust standard errors

Model (RE)	Variable	Estimate	Std. Error	t value	p-value	Significance
Clustered by Country	Intercept	26.093	2.992	8.720	<0.001	***
	x_bc	2.554	0.625	4.088	<0.001	***
Clustered by Time	Intercept	26.093	7.202	3.623	<0.001	***
	x_bc	2.554	0.714	3.577	<0.001	***

Note: Dependent variable = EGDI (Yeo–Johnson transformed). Independent variable = AIVS (Box–Cox transformed). Robust standard errors clustered by country and by year are reported. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Table 4. Correlated RE (Mundlak specification)

Variable	Estimate	Std. Error (clustered)	t value	p-value	Significance
Intercept	20.098	3.011	6.674	<0.001	***
x_bc (within)	0.244	0.950	0.257	0.798	
xb_mean (between)	3.938	1.284	3.067	0.003	**

Note: Model statistics: N = 108 (36 countries, T = 3); $R^2 = 0.189$ (Adj. $R^2 = 0.174$); Wald $\chi^2(2) = 24.53$, $p < 0.001$. Dependent variable = EGDI (Yeo–Johnson transformed). Independent variable = AIVS (Box–Cox transformed). Robust standard errors clustered by country are reported. ***, ** indicate significance at 1% and 5% levels; n.s. = not significant. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

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The estimated country-specific effects derived from the Mundlak (Table 5) correlated random effects specification reveal substantial heterogeneity in how the AI Vibrancy Score translates into E-Government Development Index outcomes across countries. Positive values of the country effect indicate that, conditional on AI vibrancy, a country exhibits a higher level of e-government development than predicted by the average relationship. In contrast, negative values reflect underperformance relative to the model benchmark. Several digitally advanced economies display strong positive deviations, most notably Denmark, the Republic of Korea, New Zealand, Australia, Sweden, Estonia, and Finland. These results suggest that in these countries, vibrant AI ecosystems are complemented by effective institutional frameworks, digital skills, and public sector capabilities that allow AI-related advances to be converted into tangible improvements in digital public administration.

By contrast, several countries exhibit markedly negative country effects, including India, Ireland, Luxembourg, Malaysia, Israel, Belgium, Canada, and Singapore. For these cases, high or moderate levels of AI vibrancy do not fully translate into commensurate e-government development, pointing to potential institutional, regulatory, or organizational bottlenecks. This pattern reinforces the interpretation that AI vibrancy alone is insufficient to guarantee progress in digital public administration; rather, its impact depends on complementary factors, such as governance quality, administrative capacity, policy coherence, and the integration of AI solutions into public service delivery. Overall, the distribution of country effects underscores the central conclusion of the study: while AI vibrancy is a significant driver of e-government development on average, national institutional contexts critically shape the extent to which AI-related capabilities are effectively transformed into digital governance outcomes.

The extended Mundlak correlated random effects model (Table 6), with explicit time controls, provides further insight into how AI vibrancy relates to e-government development, once both between-country differences and common temporal shocks are considered. The variance decomposition indicates that unobserved country-specific heterogeneity dominates the error structure, with individual effects accounting for approximately 87% of the total variance, while idiosyncratic shocks account for only 13%. This confirms that persistent national characteristics play a major role in shaping levels of e-government development. The overall model fit is high ($R^2 \approx 0.58$), suggesting that the combined inclusion of AI vibrancy, its country-level mean, and time effects captures a substantial share of the variation in the dependent variable.

Table 5. Country-specific effects (u_i) from the Mundlak correlated random effects model

No.	Country	Country effect (u_i)	No.	Country	Country effect (u_i)
1	The United Arab Emirates	–1.070	19	Luxembourg	–11.003
2	Australia	10.893	20	Malaysia	–10.225
3	Austria	0.499	21	Mexico	–5.774
4	Belgium	–6.897	22	The Netherlands	7.947
5	Brazil	0.763	23	New Zealand	12.024
6	Canada	–6.863	24	Norway	–1.354
7	China	–5.150	25	Poland	3.349
8	Denmark	16.794	26	Portugal	–6.999
9	Estonia	8.266	27	The Russian Federation	2.366
10	Finland	7.724	28	Saudi Arabia	–2.851
11	France	5.253	29	Singapore	–7.492
12	Germany	3.158	30	South Africa	–7.320
13	India	–13.394	31	Spain	5.693
14	Ireland	–11.150	32	Sweden	8.420
15	Israel	–9.915	33	Switzerland	–5.985
16	Italy	0.000	34	Turkiye	–4.824
17	Japan	7.748	35	The United Kingdom	3.680
18	Korea, Republic	13.090	36	The United States	0.596

Turning to the coefficients, the within-country component of AI vibrancy (x_bc) is statistically insignificant once year effects are introduced, whereas the between-country component (xb_mean) is positive and highly significant. This pattern suggests that cross-country differences in average AI vibrancy, rather than short-term fluctuations within countries, are the primary driver of e-government development in this specification. In other words, countries that are structurally more vibrant in AI tend to achieve systematically higher levels of digital public administration, even after controlling for common time trends. The strong and significant year dummies for 2020 and 2022 indicate pronounced global improvements in e-government development relative to the base year, likely reflecting the accelerated digitalization of public services during and after the COVID-19 period.

The extracted time effects reinforce this interpretation, showing sizable positive shifts in both 2020 and 2022, with a stronger effect in 2022. These common shocks suggest that global or region-wide forces, such as emergency-driven digital reforms, increased reliance on online public services, and international diffusion of digital governance practices, played a substantial role in raising EGDI scores across countries.

Table 6. Mundlak correlated random effects model with time effects

Variable	Estimate	Std. Error	z-value	p-value	Significance
Intercept	15.057	3.495	4.309	<0.001	***
AI Vibrancy (within, *x_bc*)	–0.409	0.708	–0.578	0.564	n.s.
AI Vibrancy (between, *xb_mean*)	4.591	1.103	4.163	<0.001	***
Year 2020	7.025	0.872	8.058	<0.001	***
Year 2022	8.096	0.811	9.981	<0.001	***

Model diagnostics

Statistic	Value
Countries (n)	36
Years (T)	3
Observations (N)	108
R^2	0.580
Adjusted R^2	0.564
χ^2 (df = 4)	142.50
p-value (χ^2)	<0.001
Share of variance (individual effects)	0.87
Share of variance (idiosyncratic)	0.13

Note: Dependent variable: E-Government Development Index (Yeo–Johnson transformed). AI Vibrancy is Box–Cox transformed. The Mundlak specification decomposes AI vibrancy into within-country (x_bc) and between-country (xb_mean) components. Year dummies capture common time shocks. *** and ** denote significance at the 1% and 5% levels.

Table 7. Country-specific intercepts (α_i) from the Mundlak correlated random effects model

Country	α_i	Country	α_i	Country	α_i
Denmark	56.21	Japan	41.32	Belgium	27.22
Korea, Republic	51.53	Norway	39.09	The Russian Federation	27.75
Australia	49.57	France	38.36	Saudi Arabia	25.19
Finland	49.02	Spain	36.83	China	21.94
Sweden	47.77	Switzerland	36.73	Turkiye	21.23
New Zealand	47.50	Austria	36.37	Malaysia	20.75
Estonia	46.17	Germany	36.57	Brazil	21.78
The United Kingdom	46.09	The United Arab Emirates	35.43	Mexico	17.00
The Netherlands	45.69	Poland	30.47	South Africa	14.94
The United States	44.02	Italy	29.65	India	7.68
Singapore	42.52	Portugal	27.97		

Note: Country-specific intercepts (α_i) represent baseline levels of E-Government Development after controlling for AI vibrancy (within and between components) and common time effects. Higher values indicate a structurally stronger performance in digital public administration.

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Finally, the country-specific intercepts (α_i, Table 7) reveal marked heterogeneity in baseline e-government performance. Countries such as Denmark, the Republic of Korea, Australia, Finland, Sweden, and New Zealand display particularly high intercepts, indicating a structurally strong position in digital public administration even after accounting for AI vibrancy and time effects. By contrast, lower intercepts for countries such as India, Mexico, South Africa, and Malaysia suggest enduring institutional or infrastructural constraints. Overall, these results underscore that while AI vibrancy is an important structural determinant of e-government development, its impact is strongly conditioned by country-specific contexts and reinforced by broad, time-related factors.

3.2. Government AI Readiness Index and E-Government Development Index

The dataset comprises 510 observations spanning 170 countries over the period 2003–2024. The variable country has a mean of 85.51 with a standard deviation of 49.11, confirming a balanced cross-sectional structure. At the same time, the median (85.50) equals the mean, indicating a symmetric distribution of country identifiers. The year variable is centered on 2022 (mean 2021.9, median 2022) and ranges from 2003 to 2024. The significant negative skewness (–3.61) and high kurtosis (29.17) reflect the concentration of observations in recent years, which is consistent with the expansion of e-government and AI readiness datasets over time.

The EGDI (Table 8) exhibits a mean of 0.64 and a standard deviation of 0.21, suggesting moderate dispersion across countries. The median value of 0.67 lies slightly above the mean, with skewness (–0.31) indicating a mild concentration toward higher levels of e-government development. The kurtosis (–0.98) indicates a relatively flat distribution, unlike a normal distribution. Overall, the EGDI values range from 0.16 to 0.98, highlighting significant differences in digital governance capacity between lagging and leading countries.

The GARI (Table 8) shows greater variability, with a mean of 46.14 and a standard deviation of 16.81. The distribution ranges from 13.46 to 87.03, indicating substantial global disparities in preparedness for AI adoption in the public sector. The skewness of 0.45 indicates a slight right-tailed distribution, with several countries attaining relatively high readiness scores. At the same time, the negative kurtosis (–0.88) indicates a broader, less peaked distribution compared to the normal distribution. This implies that AI readiness is more unevenly spread globally, with a significant cluster of countries situated at medium to low levels, and only a few achieving very high scores.

Table 8. Descriptive statistics of the dataset GARI and EGDI

Variable	EGDI (y)	GAIRI (x)
N	510	510
Mean	0.64	46.14
SD	0.21	16.81
Median	0.67	41.83
Trimmed	0.65	45.22
MAD	0.25	17.19
Min	0.16	13.46
Max	0.98	87.03
Range	0.83	73.57
Skew	−0.31	0.45
Kurtosis	−0.98	−0.88
SE	0.01	0.74

The results of the Shapiro–Wilk tests indicate that both variables deviate significantly from normality. For the GAIRI (x), the test produced a W statistic of 0.950 with a p-value < 0.001, while the EGDI (y) yielded a W statistic of 0.959 with a p-value < 0.001. In both cases, the null hypothesis of normality is rejected, suggesting that the distributions are non-Gaussian. This highlights the need for data transformations or robust econometric techniques to ensure valid statistical inference in subsequent panel estimations.

Normality tests indicated that the GAIRI (x) and the EGDI (y) deviated significantly from a Gaussian distribution, necessitating the application of appropriate transformations. The Box–Cox procedure identified an optimal λ of approximately 0.18 for the GAIRI, suggesting that a transformation close to the logarithmic form was required. This adjustment effectively reduced the right-skewness observed in the original distribution, improving its suitability for econometric modelling. In contrast, the EGDI produced an optimal λ of about 1.23, close to unity. This result indicates that the series was already approximately regular, requiring only a minor power adjustment to correct for residual skewness. The transformations enhanced the distributional properties of both variables, ensuring they are more consistent with the assumptions of panel regression analysis.

The Box–Cox transformations improved the distributional properties of both variables, but did not fully achieve normality. For the EGDI (y), the Shapiro–Wilk statistic increased slightly to 0.961 with a p-value < 0.001, indicating a partial reduction in skewness. However, the null hypothesis of normality still had to be rejected. The GAIRI Index (x) showed a more notable improvement, with $W = 0.975$ ($p < 0.001$), indicating that the transformation substantially reduced asymmetry, even though perfect normality was not achieved. The Yeo–Johnson transformations improved the distributional characteristics of both variables, although, as with the Box–Cox adjustments, strict normality was not achieved. For the GAIRI (x), the Shapiro–Wilk statistic after transformation was 0.975 ($p < 0.001$), essentially identical to the Box–Cox result, confirming that both transformations mitigate right-skewness to a similar extent. For the EGDI (y), the Yeo–Johnson transformation yielded $W = 0.964$ ($p < 0.001$), slightly higher than the Box-Cox-adjusted value, indicating a modest improvement in normality. The Yeo–Johnson transformation is more flexible as it can handle zero or negative values, but the benefits over Box–Cox are marginal. Since neither transformation fully normalized the data, robust estimation strategies remain necessary in subsequent econometric modelling.

The results of the fixed and random effects estimations with cluster-robust standard errors provide consistent evidence of a statistically significant positive association between the GAIRI and the EGDI. In the fixed effects model, the coefficient on x_yj was estimated at 0.17 and remained highly significant ($p < 0.001$) under clustering by country and year. The effect size is moderate, suggesting that increases in AI readiness within a given country are systematically associated with higher levels of e-government development over time. The slightly higher standard error when clustering by time reflects the limited temporal coverage of the dataset, but does not undermine the robustness of the result.

The random effects model, by contrast, produced a larger coefficient of approximately 0.35 for x_yj, which was also highly significant across both clustering approaches ($p < 0.001$). The negative and considerable intercept reflects differences in baseline levels of e-government development once cross-sectional heterogeneity is considered. The magnitude of the RE coefficient, roughly double that of the FE estimate, highlights that much of the observed relationship is driven by persistent cross-country differences in AI readiness rather than within-country variation.

The findings (Table 9) suggest that AI readiness is an essential driver of e-government development, but the effect size depends on the modelling strategy. The FE model isolates within-country dynamics, while the RE model captures both within- and between-country variation. The robustness of the results under both country and time clustering confirms that the association is not an artefact of heteroskedasticity or serial correlation.

The results of the Mundlak specification (Table 10) reveal essential insights into the distinction between within- and between-country effects. In the fixed effects Mundlak model, the GAIRI (x_yj)

Table 9. FE and RE estimations with cluster-robust standard errors

Model	Variable	Estimate	Std. Error	t value	p-value	Significance
FE (cluster by country)	x_yj	0.169	0.029	5.825	<0.001	***
RE (cluster by country)	Intercept	–0.952	0.135	–7.052	<0.001	***
	x_yj	0.347	0.026	13.586	<0.001	***
FE (cluster by time)	x_yj	0.169	0.037	4.607	<0.001	***
RE (cluster by time)	Intercept	–0.952	0.121	–7.846	<0.001	***
	x_yj	0.347	0.025	14.113	<0.001	***

Note: Dependent variable = EDGI (Yeo–Johnson transformed). Independent variable = GAIRI (eo–Johnson transformed). Robust standard errors clustered by country and by time are reported. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

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coefficient was estimated at 0.17. The association remained highly significant (p < 0.001), confirming that within-country increases in AI readiness are strongly linked to improvements in the EGDI. By contrast, the coefficient on the country-level mean of AI readiness (xb_mean) was small (–0.003) and statistically insignificant (p = 0.60), indicating that persistent differences in average AI readiness across countries do not independently explain variations in e-government development once within-country changes are accounted for.

The random effects Mundlak model yielded a larger coefficient for x_yj (0.35, p < 0.001), reflecting the combined influence of within- and between-country variation; however, the xb_mean variable remained statistically insignificant. The insignificance of the effect in both models suggests that the strong positive relationship identified in earlier RE specifications is not primarily driven by structural cross-country differences but by genuine within-country dynamics. These findings further support the fixed effects framework, showing that AI readiness enhances e-government development over time within countries, while cross-sectional disparities play a limited role once panel structure is considered.

The estimated country-specific effects (Table 11 and full Table B1 in Appendix B) reveal substantial heterogeneity in baseline e-government performance after accounting for differences in Government AI Readiness and global time shocks. Positive values of the country effect indicate that a country attains a higher level of e-government development than predicted by its AI readiness alone. In contrast, negative values signal underperformance relative to the model benchmark. Among the strongest positive deviations are Iceland, Denmark, New Zealand, Estonia, Belgium, Kazakhstan, and Australia, suggesting that these countries are particularly effective at converting AI-related capabilities into tangible digital public administration outcomes. This pattern underscores the significance of complementary institutional factors, including administrative capacity, interoperability of public systems, regulatory coherence, and digital skills, which enhance the impact of AI readiness on e-government development.

Conversely, several countries exhibit markedly negative effects, including Belize, Niger, Djibouti, Benin, Mauritania, and Ethiopia. In these cases, improvements in AI readiness do not translate proportionately into e-government development, suggesting structural bottlenecks. These may include weak institutional coordination, limited public-sector digital absorption capacity, or constraints in infrastructure and governance quality. Overall, the distribution of country effects underscores a central conclusion of the study: while AI readiness is a statistically significant driver of e-government development on average, national contexts critically shape outcomes. The effectiveness with which AI readiness is transformed into digital public administration progress depends less on the level of readiness per se and more on the surrounding institutional and governance environment.

Due to the very short time dimension (T = 3), a Mundlak correlated random effects specification including time fixed effects is not identified, as country means become linearly dependent on time dummies. Following standard panel econometric guidance, time effects are therefore modelled within a two-way fixed effects framework. At the same time, the Mundlak specification is used separately to decompose within- and between-country effects, without the inclusion of time dummies.

Table 10. Mundlak specifications (FE and RE) with cluster-robust standard errors

Model	Variable	Estimate	Std. Error	t value	p-value	Significance
FE Mundlak	x_yj	0.169	0.029	5.757	<0.001	***
	xb_mean	–0.003	0.006	–0.528	0.598	
RE Mundlak	Intercept	–0.937	0.126	–7.446	<0.001	***
	x_yj	0.347	0.026	13.436	<0.001	***
	xb_mean	–0.003	0.006	–0.498	0.619	

Note: Dependent variable = EDGI (Yeo–Johnson transformed). Independent variable = GAIRI (eo–Johnson transformed). Robust standard errors clustered by country and by time are reported. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Table 11. Countries with the highest and lowest country effects (u_i)

Rank	Top 10 positive effects		Panel B. Bottom 10 negative effects	
	Country	u_i	Country	u_i
1	Iceland	0.297	Belize	−0.410
2	Denmark	0.248	Niger	−0.335
3	New Zealand	0.240	Djibouti	−0.353
4	Estonia	0.236	Benin	−0.331
5	Belgium	0.238	Mauritania	−0.324
6	Kazakhstan	0.323	Ethiopia	−0.295
7	Australia	0.185	Chad	−0.290
8	Bahrain	0.186	India	−0.267
9	Uruguay	0.186	Mali	−0.270
10	Austria	0.118	Lao PDR	−0.247

Note: Positive (negative) values denote over- (under-) performance in EGDI relative to the level predicted by GAIRI, controlling for time effects.

The estimated country fixed effects (α_i, Table 12 and full Table B2 in Appendix B) indicate substantial cross-national heterogeneity in baseline e-government development after controlling for the Government AI Readiness Index and common time influences embedded in the panel structure. Positive fixed effects imply that a country's E-Government Development Index (EGDI) is systematically higher than predicted by its AI readiness alone. In contrast, negative effects signal persistent underperformance relative to the model benchmark. The dispersion is sizeable (roughly from about −0.51 to +0.47), confirming that structural, country-specific factors, such as administrative capacity, institutional quality, service delivery infrastructure, and the ability to operationalize digital reforms, remain decisive for e-government outcomes beyond what is captured by AI readiness.

The countries with the strongest positive effects (e.g., Denmark, Iceland, Estonia, the Republic of Korea, Singapore, New Zealand, Australia, and Kazakhstan) appear to convert AI readiness into digital public administration performance particularly effectively, suggesting that mature public-sector digital ecosystems and governance capabilities complement readiness. In contrast, the most negative effects (e.g., Niger, Chad, Djibouti, Ethiopia, Mauritania, Comoros, and Haiti) indicate enduring barriers that inhibit the translation of AI readiness into higher EGDI levels, pointing to constraints such as weak institutional coordination, limited human capital and infrastructure, or broader governance fragilities. Overall, these fixed effects reinforce the study's core interpretation: AI readiness is an important driver of e-government development, but the realized gains depend heavily on persistent country characteristics that shape the effectiveness of implementation.

Table 12. Countries with the highest and lowest fixed effects (α_i)

Rank	Top 10 positive effects		Panel B. Bottom 10 negative effects	
	Country	α_i	Country	α_i
1	Denmark	0.474	Niger	−0.506
2	Iceland	0.459	Chad	−0.502
3	Estonia	0.440	Djibouti	−0.464
4	Korea, Republic	0.420	Gambia	−0.453
5	New Zealand	0.421	Ethiopia	−0.427
6	Singapore	0.346	Mauritania	−0.426
7	Japan	0.336	Comoros	−0.418
8	Norway	0.331	Guinea-Bissau	−0.411
9	Spain	0.330	Benin	−0.399
10	The United Arab Emirates	0.329	Mali	−0.396

Note: α_i are country fixed effects from the fixed-effects panel specification (dependent variable: EGDI; explanatory variable: Government AI Readiness Index). Positive (negative) values denote structural overperformance (underperformance) in EGDI relative to the level predicted by AI readiness.

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The results provide consistent support for the hypothesized link between artificial intelligence and the development of e-government. In line with H1, the fixed effects estimations showed that within-country improvements in AI readiness are significantly and positively associated with higher levels of e-government development. This effect remained robust when cluster-robust standard errors were applied, confirming that the observed relationship is not an artefact of heteroskedasticity or serial correlation. The magnitude of the FE coefficient was moderate, suggesting that incremental national progress in AI readiness translates into steady improvements in digital governance performance.

By contrast, the random effects models produced larger coefficients, reflecting the role of structural cross-country differences. These findings partially support H2, as countries with persistently higher levels of AI readiness tend to achieve stronger e-government outcomes. However, the Mundlak specifications indicated that the between-country component of AI readiness was statistically insignificant, implying that cross-sectional disparities play a limited role once within-country dynamics are considered. This reinforces the interpretation that the primary driver of e-government development is the trajectory of domestic improvements in AI readiness rather than static differences between countries.

Finally, the robustness of the results across clustering strategies supports H3. Although diagnostic tests revealed challenges such as serial correlation and cross-sectional dependence, the positive relationship between AI readiness and e-government development remained stable under robust inference. The findings confirm that artificial intelligence readiness is a significant determinant of digital public administration, with the most substantial evidence pointing to the impact of ongoing national reforms and investments rather than inherited structural advantages.

4. DISCUSSION

The empirical findings of this study both confirm and refine existing research on the role of artificial intelligence in digital public administration. The positive and statistically significant within-country effect of Government AI Readiness on e-government development is consistent with studies emphasizing that AI contributes to public-sector performance when embedded in governance capabilities and institutional learning. Prior research highlights that AI readiness enhances public administration by strengthening coordination capacity, facilitating data-driven decision-making, and improving service delivery effectiveness, rather than solely through technological sophistication (Androniceanu, 2024; Murko et al., 2024). The present fixed-effects and Mundlak results extend this literature by demonstrating that changes in AI readiness over time, rather than cross-country differences in average readiness, drive improvements in the E-Government Development Index.

At the same time, the findings diverge from a substantial body of cross-sectional and comparative research that attributes higher digital governance outcomes primarily to structural national advantages in AI development. Several studies report strong between-country associations between AI maturity and governance quality, competitiveness, or innovation capacity (Jarzębowski et al., 2024; Iuga & Socol, 2024). In contrast, the Mundlak specifications in this study show that between-country (average) AI readiness effects are statistically insignificant once within-country dynamics are controlled. This suggests that earlier cross-country findings may partly capture persistent institutional characteristics, such as administrative traditions or baseline digital capacity, rather than the causal effect of AI readiness itself. In this sense, the results support recent critical perspectives arguing that AI indicators often proxy broader governance quality unless explicitly modelled in a dynamic panel framework (Bondar et al., 2024).

The statistically significant time effects observed for 2020 and 2022 are also consistent with the literature, which documents an acceleration of digital public administration during periods of systemic shock. Studies focusing on pandemic-induced digitalization highlight that governments expanded online services, interoperability, and digital identity infrastructures at an unprecedented pace, often independently of prior AI maturity (Stender et al., 2024; Yarovenko et al., 2024b). However, the persistence of a positive within-country AI readiness effect after controlling for these time shocks aligns with findings that AI-enabled governance reforms amplify the benefits of crisis-driven digital acceleration rather than merely coinciding with it (Kuzior et al., 2025). This reinforces the argument that AI readiness functions as a catalyst, allowing governments to convert external pressures into sustained administrative improvement.

Finally, the pronounced country-specific effects identified in the Mundlak framework resonate with the literature emphasizing institutional heterogeneity in AI adoption outcomes. Research on public-sector AI repeatedly emphasizes that legal frameworks, administrative culture, ethical governance, and public trust significantly influence the effectiveness of AI-driven reforms (Haley, 2025; Haley & Burrell, 2025; Mura & Stehlíková, 2025). Countries that outperform predictions based on AI readiness alone appear to possess complementary institutional assets. In contrast, underperforming countries face structural constraints that limit the translation of AI readiness into effective e-government outcomes. Thus, the results corroborate the growing consensus in the literature that AI readiness is a necessary but insufficient condition for digital public administration success, and that its impact is contingent upon broader governance ecosystems rather than technology-led strategies alone.

This study is subject to several limitations. First, the temporal scope is narrow: the AI Vibrancy Score covers only the period from 2018 to 2022, and the Government AI Readiness Index from 2019, whereas the E-Government Development Index is updated biennially. This restricts the ability to observe long-term effects of AI on public administration. Second, the analysis relies on composite indices (AIVS, GAIRI, and EGDI) that, despite their authority, may not fully capture national particularities or qualitative aspects of governance. Third, the absence of additional control variables, such as GDP, ICT penetration, or institutional quality, increases the risk of omitted-variable bias. Finally, the short panel dimension and cross-sectional dependence limit efficiency, even with robust estimation techniques. Future research should extend the time horizon, incorporate richer covariates, and combine quantitative with qualitative approaches.

CONCLUSION

This study aimed to investigate whether the vibrancy and readiness of artificial intelligence act as drivers of digital public administration, as measured by their impact on the EGDI. The analysis aimed to distinguish between within-country dynamics and cross-country disparities while assessing the robustness of the relationship under alternative model specifications.

Two complementary panels were analyzed: 36 countries (2018–2022) linking AIVS with EGDI, and 170 countries (2020–2024) combining GAIRI with EGDI. The study applied panel econometric models (fixed, random, and Mundlak) with robust, cluster-adjusted inference.

The results show a robust positive relationship between AI development and e-government performance. Within-country estimates indicate that improvements in AI readiness increase EGDI (FE coefficient for GAIRI = 0.17, $p < 0.001$), while random effects suggest stronger cross-country associations (2.55 for AIVS and 0.35 for GAIRI, $p < 0.001$). However, Mundlak models indicate that between-country effects are insignificant, suggesting that progress is driven mainly by within-country reforms rather than structural advantages, and that the results remain robust under clustered errors. The analysis also highlights strong country heterogeneity and time effects. Unobserved country factors explain most of the variance (≈87%), indicating persistent structural differences, while positive and significant time effects show that EGDI increased by about 7.0 points in 2020 and 8.1 points in 2022, reflecting a global upward trend in digital governance beyond AI influences.

These results carry important policy implications. First, governments should recognize that advancing AI readiness is an innovation or industrial policy priority and a crucial enabler of more effective and

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accessible digital public services. Second, policy efforts should focus on sustained domestic investments, such as building digital infrastructure, developing human capital, and strengthening institutional frameworks for AI governance, since within-country dynamics drive most of the observed improvements. Third, international cooperation and benchmarking remain valuable, but the evidence suggests that internal reforms are more decisive than structural differences across states. Finally, policies aimed at inclusive capacity-building in AI should be integrated into national digital transformation strategies to ensure that progress in e-government development is broad-based, resilient, and aligned with social and economic development goals.

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APPENDIX A

Samples of the countries for analysis

List of the countries in the sample for analysis of the interrelation of AI Vibrancy Index and EGDI:

United Arab Emirates, Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Estonia, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, the Republic of Korea, Luxembourg, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Russian Federation, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Turkiye, the United Kingdom, and the United States.

List of the countries in the sample for analysis of the interrelation of GAIRI and EGDI:

Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Chad, Chile, China, Colombia, Comoros, Congo (Rep.), Costa Rica, Côte d'Ivoire, Croatia, Cuba, Cyprus, Czechia, the Democratic Republic of the Congo, Denmark, Djibouti, the Dominican Republic, Ecuador, Egypt (Arab Rep.), El Salvador, Estonia, Eswatini, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran (Islamic Rep.), Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, the Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, the Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, the Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Paraguay, Peru, the Philippines, Poland, Portugal, Qatar, the Republic of Korea, Moldova, Romania, the Russian Federation, Rwanda, Saint Lucia, Saint Vincent and the Grenadines, Samoa, Saudi Arabia, Senegal, Serbia, the Seychelles, Sierra Leone, Singapore, the Slovak Republic, Slovenia, Solomon Islands, South Africa, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, the Syrian Arab Republic, Tajikistan, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkiye, Uganda, Ukraine, the United Arab Emirates, the United Kingdom, Tanzania, the United States, Uruguay, Uzbekistan, Vanuatu, Venezuela (RB), Viet Nam, Yemen (Rep.), Zambia, and Zimbabwe.

APPENDIX B

Country-specific effects

Table B1. Country-specific effects (u_i) from the Mundlak correlated random effects model

Country	u_i	Country	u_i	Country	u_i
Afghanistan	−0.061	Oman	0.092	Germany	0.066
Angola	−0.169	Panama	0.101	Greece	0.185
Argentina	0.176	Peru	0.119	Guatemala	−0.045
Australia	0.185	Poland	0.110	Guinea-Bissau	−0.228
Azerbaijan	0.112	Qatar	−0.056	Haiti	−0.142
Bangladesh	−0.079	Russian Federation	0.087	Hungary	0.028
Belarus	0.208	Saint Lucia	−0.073	India	−0.267
Belize	−0.410	Samoa	−0.158	Iran, Islamic Rep.	−0.009

Table B1 (cont.). Country-specific effects (u_i) from the Mundlak correlated random effects model

Country	u_i	Country	u_i	Country	u_i
Bhutan	−0.005	Senegal	−0.227	Ireland	0.080
Bosnia and Herzegovina	0.074	Seychelles	0.051	Italy	0.026
Brazil	0.075	Singapore	0.097	Japan	0.121
Bulgaria	0.078	Slovenia	0.174	Kazakhstan	0.323
Burundi	−0.130	South Africa	0.110	Korea, Republic	0.185
Cambodia	−0.035	Sri Lanka	0.055	Kyrgyz Republic	0.203
Canada	−0.019	Suriname	−0.005	Latvia	0.134
Chile	0.150	Switzerland	0.129	Lesotho	−0.107
Colombia	−0.015	Tajikistan	−0.111	Luxembourg	0.035
Congo, Dem. Rep.	−0.154	Thailand	0.037	Malawi	−0.163
Costa Rica	0.152	Togo	−0.153	Maldives	0.064
Croatia	0.218	Trinidad and Tobago	0.093	Malta	0.172
Cyprus	0.197	Turkiye	0.150	Mauritius	0.069
Denmark	0.248	Ukraine	0.126	Moldova	0.091
Dominican Republic	0.032	United States	0.042	Montenegro	0.079
Egypt, Arab Rep.	−0.181	Uzbekistan	0.117	Mozambique	−0.152
Estonia	0.236	Venezuela, RB	0.045	Namibia	−0.005
Ethiopia	−0.295	Yemen, Rep.	−0.020	Netherlands	0.165
Finland	0.171	Zimbabwe	−0.057	Nicaragua	0.019
Gabon	−0.009	United Arab Emirates	0.127	Nigeria	−0.213
Georgia	0.163	Algeria	−0.037	Norway	0.118
Ghana	−0.021	Antigua and Barbuda	0.002	Pakistan	−0.229
Grenada	0.123	Armenia	0.198	Paraguay	0.127
Guinea	−0.225	Austria	0.118	Philippines	−0.029
Guyana	−0.059	Bahrain	0.186	Portugal	0.034
Honduras	−0.118	Barbados	0.135	Romania	0.052
Iceland	0.297	Belgium	0.238	Rwanda	−0.183
Indonesia	−0.051	Benin	−0.331	Saint Vincent and the Grenadines	−0.001
Iraq	−0.195	Bolivia	0.130	Saudi Arabia	0.154
Israel	0.083	Botswana	−0.037	Serbia	0.131
Jamaica	−0.004	Brunei Darussalam	0.044	Sierra Leone	−0.221
Jordan	−0.171	Burkina Faso	−0.231	Slovak Republic	0.072
Kenya	−0.111	Cabo Verde	−0.012	Solomon Islands	−0.209
Kuwait	0.123	Cameroon	−0.137	Spain	0.147
Lao PDR	−0.247	Chad	−0.290	Sudan	−0.189
Lebanon	−0.193	China	−0.004	Sweden	0.161
Lithuania	0.159	Comoros	−0.250	Syrian Arab Republic	0.149
Madagascar	−0.217	Congo, Rep.	−0.162	Tanzania	−0.193
Malaysia	−0.036	Cote d'Ivoire	−0.054	Timor-Leste	−0.163
Mali	−0.270	Cuba	−0.137	Tonga	−0.101
Mauritania	−0.324	Czechia	0.019	Tunisia	0.001
Mexico	−0.000	Djibouti	−0.353	Uganda	−0.150
Mongolia	0.213	Ecuador	0.217	United Kingdom	0.126
Morocco	−0.004	El Salvador	0.062	Uruguay	0.186
Myanmar	−0.104	Eswatini	0.014	Vanuatu	−0.077
Nepal	−0.014	Fiji	0.027	Viet Nam	−0.023
New Zealand	0.240	France	0.037	Zambia	−0.112
Niger	−0.335	Gambia	−0.321	Kiribati	−0.086
North Macedonia	0.069				

Note: u_i are country-specific intercepts from the Mundlak correlated RE model with time effects. Positive values denote structural overperformance in EGDI relative to GAIRI; negative values denote underperformance.

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Table B2. Country fixed effects (α_i) from the panel model

Country	α_i	Country	α_i	Country	α_i
Kiribati	−0.210	Nigeria	−0.263	Georgia	0.191
Afghanistan	−0.322	Norway	0.331	Ghana	−0.041
Algeria	−0.088	Pakistan	−0.276	Grenada	0.079
Antigua and Barbuda	−0.014	Paraguay	0.096	Guinea	−0.357
Armenia	0.225	Philippines	0.044	Guyana	−0.131
Austria	0.313	Portugal	0.205	Honduras	−0.225
Bahrain	0.290	Romania	0.144	Iceland	0.459
Barbados	0.136	Rwanda	−0.182	Indonesia	0.057
Belgium	0.295	Saint Vincent and the Grenadines	−0.053	Iraq	−0.263
Benin	−0.399	Saudi Arabia	0.311	Israel	0.277
Bolivia	0.065	Serbia	0.236	Jamaica	−0.035
Botswana	−0.082	Sierra Leone	−0.393	Jordan	−0.114
Brunei Darussalam	0.121	Slovak Republic	0.188	Kenya	−0.112
Burkina Faso	−0.366	Solomon Islands	−0.337	Kuwait	0.194
Cabo Verde	−0.052	Spain	0.330	Lao PDR	−0.337
Cameroon	−0.238	Sudan	−0.370	Lebanon	−0.200
Chad	−0.502	Sweden	0.383	Lithuania	0.325
China	0.180	Syrian Arab Republic	−0.104	Madagascar	−0.359
Comoros	−0.418	Tanzania	−0.278	Malaysia	0.129
Congo, Rep.	−0.308	Timor-Leste	−0.253	Mali	−0.396
Cote d'Ivoire	−0.131	Tonga	−0.143	Mauritania	−0.426
Cuba	−0.207	Tunisia	0.028	Mexico	0.146
Czechia	0.181	Uganda	−0.239	Mongolia	0.209
Djibouti	−0.464	United Kingdom	0.364	Morocco	−0.019
Ecuador	0.194	Uruguay	0.318	Myanmar	−0.190
El Salvador	−0.023	Vanuatu	−0.163	Nepal	−0.107
Estwatini	−0.094	Viet Nam	0.052	New Zealand	0.421
Fiji	0.029	Zambia	−0.184	Niger	−0.506
France	0.252	United Arab Emirates	0.329	North Macedonia	0.099
Gambia	−0.453	Albania	0.222	Oman	0.210
Germany	0.283	Angola	−0.341	Panama	0.110
Greece	0.292	Argentina	0.283	Peru	0.175
Guatemala	−0.113	Australia	0.406	Poland	0.268
Guinea-Bissau	−0.411	Azerbaijan	0.139	Qatar	0.079
Haiti	−0.379	Bangladesh	−0.091	Russian Federation	0.233
Hungary	0.157	Belarus	0.290	Saint Lucia	−0.120
India	−0.157	Belize	−0.347	Samoa	−0.244
Iran, Islamic Rep.	0.009	Bhutan	−0.041	Senegal	−0.266
Ireland	0.271	Bosnia and Herzegovina	0.034	Seychelles	0.068
Italy	0.201	Brazil	0.195	Singapore	0.346
Japan	0.336	Bulgaria	0.193	Slovenia	0.319
Kazakhstan	0.395	Burundi	−0.337	South Africa	0.178
Korea, Republic	0.420	Cambodia	−0.110	Sri Lanka	0.046
Kyrgyz Republic	0.166	Canada	0.192	Suriname	−0.054
Latvia	0.268	Chile	0.284	Switzerland	0.314
Lesotho	−0.222	Colombia	0.088	Tajikistan	−0.167
Luxembourg	0.221	Congo, Dem. Rep.	−0.363	Thailand	0.160
Malawi	−0.314	Costa Rica	0.210	Togo	−0.264
Maldives	0.012	Croatia	0.294	Trinidad and Tobago	0.080
Malta	0.328	Cyprus	0.327	Turkiye	0.255
Mauritius	0.087	Denmark	0.474	Ukraine	0.224
Moldova	0.134	Dominican Republic	0.052	United States	0.303

Table B2 (cont). Country fixed effects (α_i) from the panel model

Country	α_i	Country	α_i	Country	α_i
Montenegro	0.115	Egypt, Arab Rep.	−0.124	Uzbekistan	0.150
Mozambique	−0.335	Estonia	0.440	Venezuela, RB	−0.075
Namibia	−0.062	Ethiopia	−0.427	Yemen, Rep.	−0.294
Netherlands	0.388	Finland	0.404	Zimbabwe	−0.169
Nicaragua	−0.095	Gabon	−0.076		

Note: Values are rounded to three decimals.

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