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Digital Readiness and Growth: How Government AI Preparedness shapes African Economies

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Abstract

Purpose: This study investigates the impact of government AI readiness on economic growth, with a particular focus on the roles of government, the technology sector, and data & infrastructure. It aims to provide a nuanced analysis of the digital readiness-growth nexus and evaluate whether artificial intelligence in government acts as a catalyst for or a constraint on African economic growth.

Design/Methodology/Approach: The study employs an econometric analysis, namely the GMM system. The analysis is conducted on a panel of 44 African countries over the period 2020–2024, capturing the dynamic relation between government AI readiness indicators and economic growth.

Findings: The main result is that economic growth in the African countries is strongly dependent on its past values, while the direct contribution of government, technology sector, and data & infrastructure does not emerge as significant within the short timeframe examined.

Practical Implications: Policymakers should promote the application of AI in African governments by strengthening governance through robust legal frameworks, transparent digital strategies, and technology development through the digitization of public services. As well as effective data management and infrastructure improvement.

Originality/Value: This study provides new empirical evidence on the relation between the digital readiness in government and growth in African economies, considering multiple dimensions of government AI readiness and utilizing a robust econometric approach (GMM system). It contributes to the debate on digital readiness by distinguishing between government, the technology sector, data, and infrastructure.

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INTRODUCTION

Artificial intelligence (AI) has significantly enhanced human capabilities to carry out complicated tasks from various domains such as infrastructure, data ecosystem, digital economy, healthcare, environmental sustainability, and agriculture. Advancements in AI offer a chance to create better solutions to solve current societal challenges and have long-term beneficial impacts (Kondo and Diwani 2023).

Recent years have witnessed a growing scholarly focus on "artificial intelligence" (AI) in public administration, driven by the emergence of Big Data and the automation of work via "digital information and communication technologies" (ICT) (Ingrams 2021, p. 390). Incorporating AI technologies into government functions has huge benefits. One major benefit is that it makes administration more efficient, which is a key part of providing good public services Alhosani and Alhashmi 2024. Especially since, over the past few decades, the acceptance of AI in the public sector has been delayed than in the private sector. As a result, interest in using AI in government is relatively new. (Desouza & al, 2020). AI methods and digital transformation initiatives from the private sector cannot directly be translated to the public sector because of the public sector's obligation to maximize public benefit. Compared to the private sector, there is less understanding of addressing AI concerns directly related to the public sector (Zuiderwijk et al. 2021). AI can streamline processes, such as automating bureaucratic tasks, which improves response times and reduces human error (Coelho and Silva 2024), and also Large-scale data processing enables better resource management and informed policy-making, enhancing transparency (Söker 2024; Coelho and Silva 2024). Furthermore, AI tools can facilitate improved communication with citizens, allowing for more targeted and effective public policies (OECD 2022). A study on UK government services estimated that 143 million complex transactions are highly automatable, potentially saving about 1200 person-years annually (Straub et al. 2024).

Artificial Intelligence (AI) is transforming economies by enhancing productivity, efficiency, and cost-effectiveness. Governments occupy a distinctive role regarding AI since they establish national strategic aims, allocate public investments, and formulate regulations. Governments have acknowledged the significance of AI and its potential applications across several sectors of the economy in the future. Over 60 nations are engaged in this endeavour (OECD 2022).

Artificial intelligence (AI) has demonstrated its value in a variety of fields and applications, making it a potentially beneficial tool for the economy, society, and government. Even while AI is becoming more and more accepted as a science or technology, intellectual and political elites have not yet fully acknowledged it as a game-changing invention. As a result, supporting the public sector in defining the scope of AI is hard (Alhosani and Alhashmi 2024). The numerous consequences of AI in government for public governance are poorly understood by most countries. Given the rapid adoption of AI applications in government worldwide, governance and AI thought leadership is shrinking. This information gap is a major development hurdle as governments grapple with the social, economic, political, and ethical effects of AI changes (Zuiderwijk et al. 2021). Artificial intelligence has been described as a "game changer" for public administration, with the potential to "disruptive" or "transformative". It has two types of effects: technical effects on technological progress, and effects on societal or ethical outcomes that characterize the quality of government-citizen relations (Maciejewski 2016; Agarwal 2018).

Most national AI policies acknowledge the significance of implementing AI in the public sector. Actually, governments are reinventing how they create and provide policies and services by utilizing AI more and more for public sector innovation and change (OECD 2022). The EU's comprehensive assessment shows that AI improves policy-making by detecting growing social challenges, overseeing implementation, and reviewing policy effectiveness (Noordt and Misuraca 2022). As a result, African countries are making national AI plans and setting up AI advisory groups to lead the way in using and developing technology (Plantinga et al. 2024).

Despite the presence of research examining government readiness for artificial intelligence, empirical findings on the causal direction of its relationship with economic growth remain inconclusive. This study contributes to the ongoing debate on the relationship between digital readiness in government and economic growth by addressing the following question: Does government readiness for artificial intelligence stimulate economic growth in the African countries under study? Based on this research question, the study hypothesizes that government AI readiness indicators have a positive impact on economic growth in the African countries under study.

LITERATURE REVIEW

Previous literature has provided mixed results on the impact of government digital readiness on economic growth. Although some studies indicate that high levels of readiness contribute positively to productivity, competitiveness, etc., some other research highlights the challenges facing the adoption of artificial intelligence in developing governments. These studies have provided diverse opinions and empirical findings that expand the scope of ongoing debate.

Some studies have adopted a descriptive analytical approach by analysing the specific factors for AI readiness and the factors that may have a direct impact on government's readiness for AI. Such as Montoya and Rivas (2019), this study compares indicators of AI technology development and use in governance, infrastructure, technological skills, and public services to each country's economic metrics. It also examines non-economic parameters that affect AI readiness and its implications on each country's population. Similarly, Alalaq (2025) focused on Iraq, discussing the challenges the Iraqi government encountered in implementing and using AI technology. The report analysed the economic, social, and political constraints inhibiting this shift and presented clear recommendations to overcome these difficulties. This report underlines the significance of investing in education, training, and capacity building to generate a trained workforce, enabling governments to harness AI potential and enhance government service efficiency. Also, Nzobonimpa and Savard (2023) this study explores the relationship between government AI preparedness and accountability, and concludes that advancement in AI is not enough to provide responsible governance, demonstrating the necessity for principles like privacy, transparency, and inclusion.

Study of Ahangama and Krishnan (2023) examines the mediating role of AI preparedness of a government in affecting the e-participation implementations of a country and its people's well-being. The empirical analysis was performed based on archival data for 72 nations. Results show that AI preparedness strengthens the positive effect of e-participation implementation on the well-being of the people. In addition, study of Seini et al. (2024) investigates the dynamic relationships between the maturity of the technology sector, human capital, and African government AI readiness. Using the Technology-Organization Environment paradigm and Partial Least Squares Structural Equation Modeling, the study analyses data from the Government AI Readiness Index 2023 of 53 African countries. Results reveal that there is a high positive correlation between government AI readiness and technology sector maturity, and between human capital and technology sector maturity. However, the relationship between government AI readiness and human capital is less strong. These findings suggest that whereas an advanced technology sector has a direct positive influence on government AI readiness, its effect through the creation of human capital is less important in the African context.

On the other hand, some other studies adopted the standard approach by using panel data such as Amin Mohamed (2024); this study looks at how AI government readiness affects economic growth using the Cobb-Douglas production function for 115 developing nations between 2020 and 2023. The study's findings demonstrate that government preparedness for AI significantly and favourably affects economic growth in developing nations. Previous studies have also linked artificial intelligence to economic growth Sarker (2022), the study employed time series data to investigate the effects of AI on the labour market and productivity. The data suggested that Bangladesh had not yet realized the projected economic merits, despite the combined number of AI-induced industry robots was insignificant. A study of Acemoglu and Pascual (2018) found that the AI has considerable effects on the labour market and employment. In the short run, given that capital is fixed, it was found that automation negatively affects employment and reduces wages. On the contrary, Wang et al. (2021) and Chih-Hai Yang (2022) found that AI technologies had a positive effect on productivity and employment. In another context, the research of Yu (2025) contained two studies that explored the influence of AI integration on economic growth in China. Study one assessed the mediating function of workforce adaptation and the moderating effect of government policy in the link between AI integration and economic growth. Study two enhanced this approach by studying technical infrastructure as a joint moderator coupled with government policy. The results suggested that Study two provided more hopeful outcomes than Study one, demonstrating a major breakthrough in the knowledge of AI integration's impact on economic growth when technology infrastructure was addressed alongside government policy.

The research conducted by Saba and Ngepah (2024) examines the impact of investment in AI on growth and employment in BRICS nations during 2012-2022. Using The CS-ARDL model. The evidence confirms the existence of long-run equilibrating relationship between the variables employed in the models of job and growth. Causality test results for our variable of interest are mixed in the employment-growth models. The findings suggest that BRICS policymakers and governments need to prioritize and scale up the use of AI in governance systems to create jobs and spur growth both in the short and long term. In addition, study of De Fegueiredo (2024) examined the role of digital readiness in shaping economic growth within the European Union, drawing on the Digital Economy and Society Index (DESI) across a sample of 22 states. The analysis indicated that human capital development and the adoption of digital technologies were key determinants of growth, whereas digital public services showed a slight negative relationship with GDP. The results indicated that development of digital capabilities and extending company utilization of technical tools were imperative to spur productivity and encourage innovation, highlighting the importance of targeted investments in digital readiness as a foundation for sustained economic growth.

According to previous studies, the research gap has been in the study of regions such as Africa, where the economic impacts of adopting artificial intelligence are still emerging.

DATA AND METHODS

This study employs the GMM system, more precisely "the two-step difference GMM approach", in conjunction with the STATA 17 software in order to analyse the impact of Government AI Readiness on economic growth across 44 African economies. The analysis spans a 5-year period (2020-2024), with the temporal scope determined by data availability constraints for key government AI readiness indicators. The study covers all African countries, excluding those with unavailable or missing data. Endogeneity, autocorrelation, and heteroskedasticity issues are handled with the GMM estimator. This approach is suitable, when the number of cross-sectional units (N) is larger than the duration (T) (Roodman 2009).

In order to accomplish the goals of the study, the following regression models are created:

$$Y_{i,t} = \beta_0 + \delta Y_{i,t-1} + \beta_1 GAIR_{i,t} + \beta_2 GOV_{i,t} + \beta_3 TECH_{i,t} + \beta_4 DINF_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where:

$Y_{i,t}$ − Gross Domestic product (GDP) of country i(1,……,44) at year t(1,….5).

β_0 − The constant parameter.

δ −The speed of adjustment to equilibrium.

$Y_{i,t-1}$ − the one-period lagged GDP.

$\beta_1 - \beta_4$ − the coefficient parameters of the model.

$\varepsilon_{i,t}$ − the model error term.

Data sources

This study relies on panel data drawn from two main sources, the World Bank's foundation (2024), which provide data on GDP as a dependent variable, and the Oxford insights, which offers measures for 4-keys independent variables, and the following table provides a detailed description of the variables used in the analysis.

Table 1. Variables and Data collection sources

Variable	Source	Measurement
Economic growth (GDP)	World Bank database	GDP (constant 2015 US$)
Government AI Readiness (GAIR)	Oxford insights Data	Composite measure derived from government, technology, and data infrastructure dimensions, using normalized and weighted indicators to generate a final readiness score. Countries are ranked on a 0–100 scale, where higher scores indicate greater AI readiness
Government (GOV)	Oxford insights Data	Measures the readiness of state institutions to develop policies and strategies related to artificial intelligence. Includes sub-indicators such as: national vision and strategy for AI, quality of institutions, regulatory effectiveness, and transparency. Countries are ranked on a 0–100 scale.
Technology sector (TECH)	Oxford insights Data	Measures the technological infrastructure and innovation ecosystem. Includes sub-indicators such as: Internet penetration, R&D expenditure, cybersecurity, availability of digital skills. Countries are ranked on a 0–100 scale.
Data & Infrastructure (DINF)	Oxford insights Data	Measures the Availability and quality of data and supporting infrastructure. Includes sub-indicators such as: Open data initiatives, data protection frameworks, access to digital platforms, ICT infrastructure. Countries are ranked on a 0–100 scale.

RESULT AND DISCUSSION

Given the short time dimension of the panel dataset (5 years across 44 countries), traditional panel-unit root tests such as Levin–Lin–Chu, Im–Pesaran–Shin, or Fisher-type ADF/PP suffer from low statistical power and may produce unreliable results. In such cases, the concept of stationarity remains important, but its empirical testing becomes less informative. To address this limitation, the analysis relies on transforming variables into growth rates or first-differences (e.g., log-differences) whenever non-stationarity is theoretically expected, while variables that are generally considered stationary in levels (such as ratios or rates) are maintained in their original form. This approach reduces the risk of spurious regression and ensures that the estimated relationships remain robust despite the short time span of the data.

Table 2. Descriptive Statistics

Variable	Mean	SD	Min	Max
GDP	6.23e+10	1.13e+11	1.42e+09	5.70e+11
GAIR	32.56101	7.450553	19.73651	55.62589
GOV	32.02502	12.46696	10.0215	71.4382
TECH	23.77138	5.855924	13.85716	42.12676
DINF	41.88663	8.336116	25.49187	72.22241

Source: Stata 17 software output (2025)

The descriptive statistics show that the average GDP across the sample was approximately 6.23e+10, with a standard deviation of 1.13e+11, indicating a high degree of variation among countries. The minimum GDP was 1.42e+09, while the maximum reached 5.70e+11. Government AI readiness (GAIR), the mean value was 32.56 with a standard deviation of 7.45, suggesting moderate dispersion; values ranged between 19.73 and 55.62. The government indicator (GOV) recorded a mean of 32.03, a relatively large standard deviation of 12.47, and a wide range (10.02 to 71.43), which reflects considerable heterogeneity in governance. The technology index (TECH) had an average of 23.77 and a relatively lower variability (SD = 5.86), with values spanning from 13.86 to 42.13. Finally, the data & infrastructure index (DINF) exhibited a mean of 41.89 and a standard deviation of 8.34, with values ranging between 25.49 and 72.22, suggesting a relatively more balanced distribution compared to other.

Correlation Matrix

A correlation matrix is a tool employed in econometrics to examine the patterns of correlations among variables. It signifies the presence of multicollinearity and offers a metric for the statistical significance of the correlation among the study's variables.

The results of the correlation matrix for each of the study's variables are shown in table 3, such as GDP has a significant positive association with all independent variables. GAIR demonstrates a moderate positive connection with GDP (0.5251). Similarly, GOV shows a weaker but still positive correlation with GDP (0.4315), while TECH and DINF display moderate positive correlations with GDP, at 0.4804 and 0.4254 respectively. The results also highlight the presence of strong intercorrelations among the independent variables, notably between GAIR and GOV (0.8620), GAIR and TECH (0.8277), and GAIR and DINF (0.8108). Such high correlations raise concerns about multicollinearity, which may bias regression estimates. To resolve this issue, it is important to rely on "the generalized method of moment (GMM)", to ensure the robustness of the empirical results.

Table 3. Correlation Matrix

	GDP	GAIR	GOV	TECH	DINF
GDP	1.0000				
GAIR	0.5251	1.0000			
GOV	0.4315	0.8620	1.0000		
TECH	0.4804	0.8277	0.5290	1.0000	
DINF	0.4254	0.8108	0.4441	0.7257	1.0000

Source: Stata 17 software output (2025)

Regression Analysis

"Two-step system GMM (Arellano-Bover/Blundell-Bond)" estimator was applied to address potential endogeneity and dynamic dependence in short panel data. The potential issues with "GMM estimation" are identified in this study by use of two conventional diagnostic tests, which the autocorrelation of residuals is measured by the AR1- AR2 tests, and the validity of instruments is measured by the "Sargan" test. In order to ensure that the instruments utilised are legitimate, "Sargan" is employed. That the tools utilised are external is the premise around which this test is based. Therefore, a high p-value is necessary. The autocorrelation at levels 1-2 can be detected by the Arellano and Bond autocorrelation tests (AR1-AR2). This test's null hypothesis states that, at levels 1 and 2, there is no serial correlation between the error terms. To accept the null hypothesis, p-value for AR1-AR2 tests must be greater.

Arellano-Bond autocorrelation test was employed to examine the presence of serial correlation in the differenced residuals. The results indicate that AR (1) test is statistically insignificant ($z = -1.55$, $p = 0.121$), suggesting the absence of first-order serial correlation. More importantly, the AR (2) test is also insignificant ($z = 0.09$, $p = 0.928$), which confirms the absence of second-order serial correlation in the residuals. This outcome satisfies a key requirement of the "System GMM" methodology, thereby validating the consistency of the estimator and indicating that the instruments used are not affected by excessive serial correlation.

The validity of the instruments was further assessed through the "Sargan" and "Hansen" tests of over identifying restrictions. The Sargan test yielded a statistically insignificant result ($\chi^2(12) = 18.35$, $p = 0.106$), indicating that the null hypothesis of instrument validity cannot be rejected. However, it is important to note that the Sargan test is not robust to heteroskedasticity, although it is not weakened by the limited number of instruments in this model. By contrast, the "Hansen" test, which is robust and more reliable in the presence of heteroskedasticity, also produced an insignificant result (χ^2 (12) = 15.34, $p = 0.223$). This confirms that the instruments are valid and not correlated with the error term. Taken together, these results provide strong evidence that the GMM instruments used in the estimation are appropriate and that there is no indication of instrument weakness. In addition, the Difference-in-Hansen tests for subsets of instruments confirm their validity and exogeneity, further improving the trustworthiness of the estimates.

Methodologically, a limited number of instruments (17) were adopted, which is relatively appropriate. However, the variable of government AI readiness was excluded due to multicollinearity, and its three dimensions were sufficient.

The results suggest that GDP exhibits a remarkable degree of persistence, as indicated by the very significant and positive coefficient of the lagged dependent variable (GDP (-1) = 1.037, $p = 0.000$).

This result explains why economic growth in African countries has maintained a strong continuity, which suggests that past economic performance is largely responsible for current economic performance. This result may reflect structural characteristics of African economies, such as limited diversification and institutional rigidity.

Due to the dominance of the dependent variable, the marginal explanatory power of other independent variables is reduced, indicating that structural and historical determinants of growth hold greater influence than emerging digital readiness factors in the short term. This conclusion illustrates the path dependent character of growth in the sampled African economies.

By contrast, the estimated coefficients of GOV, TECH, and DINF were statistically insignificant, implying that their direct impact on economic growth was not visible during the short research period. This outcome may be attributable to the restricted time dimension of the dataset or to the existence of indirect or non-linear correlations not captured by the model. Taking into account dynamic stability, these factors cannot have an independent, measurable effect on growth within the specified model and time horizon.

This result can be attributed to several economic explanations, the first of which is that government readiness for AI does not automatically translate into productive economic outcomes. In many African countries, AI strategies and digital policies may exist at the institutional level, yet implementation capacity, digital infrastructure, skilled human capital, and private sector uptake remain limited. Therefore, institutional readiness may not yet have reached the minimum threshold required to achieve measurable aggregate economic impacts.

African economies also continue to face structural challenges, including high informal sector rates, limited industrialization, weak research and development ecosystems, and infrastructure gaps. These constraints may weaken the transmission mechanism through which AI readiness can stimulate economic growth. In such contexts, basic development factors may overshadow digital transformation initiatives.

Table 4. Dynamic panel-data estimation, two-step system GMM

Variable	Coefficient	Corrected Std.err.	T	P- value
GDP L1.	1.037437	0.0072046	144.00	0.000
GOV	30,400,000	42,100,000	1.20	0.237
TECH	-273,000,000	320,000,000	-0.85	0.398
DINF	84,000,000	188,000,000	0.45	0.657
_Cons	1,340,000,000	2,820,000,000	0.48	0.636
N of obs	176			
N of instrument	17			

N of groups 44
AR(1): z = -1.55 Pr > z = 0.121
AR(2): z = 0.09 Pr > z = 0.928
Sargan test: chi2(12) = 18.35 Prob > chi2 = 0.106
Hansen test: chi2(12) = 15.34 Prob > chi2 = 0.223
Difference-in-Hansen tests of exogeneity of instrument subsets:
GMM instruments for levels
Hansen test excluding group: chi2(8) = 13.93 Prob > chi2 = 0.083
Difference (null H = exogenous): chi2(4) = 1.41 Prob > chi2 = 0.843
gmm(L.GDP, collapse lag(2 .))
Hansen test excluding group: chi2(9) = 8.09 Prob > chi2 = 0.525
Difference (null H = exogenous): chi2(3) = 7.25 Prob > chi2 = 0.064
iv(GAIR, eq(level))
Hansen test excluding group: chi2(11) = 15.33 Prob > chi2 = 0.168
Difference (null H = exogenous): chi2(1) = 0.01 Prob > chi2 = 0.924

Source: Stata 17 software output (2025)

CONCLUSION

This study provides empirical evidence on the impact of government AI readiness on economic growth in 44 African countries over the period 2020–2024 using the GMM system. The findings reveal that economic growth in the countries under study exhibits a high degree of dependence on its past values, reflecting path dependence. In contrast, none of the independent variables (government, technology sector, data & infrastructure) demonstrated a significant impact on economic growth during the period under study. This result is likely due to the short time series and the weak explanatory power of the variables in the short run, or to the existence of indirect or nonlinear relationships between the studied indicators and growth.

From a theoretical perspective, the findings suggest that digital readiness may represent a necessary but not sufficient condition for economic growth. Arguments that focus on absorptive capacity, institutional quality, and structural transformation as mediating factors between technological preparedness and macroeconomic performance are supported by the results. In emerging economies, the growth-enhancing effects of artificial intelligence may depend on complementary reforms in education, infrastructure, financial systems, and governance effectiveness.

Overall, Government readiness for artificial intelligence does not necessarily translate into widespread practical implementation, immediate productivity gains, or a direct contribution to gross domestic product. In many African countries, although digital strategies and policy frameworks have been introduced, critical enabling conditions—such as digital infrastructure, skilled human capital, and adequate financial resources—remain relatively limited. Therefore, the hypothesis proposing a positive and significant impact of GAIR on economic growth is not empirically supported. Consequently, the economic impact of AI readiness is more likely to emerge over the long term rather than in the short term captured by the dynamic model used in this study.

Despite government digital transformation initiatives, many African countries still suffer from a significant gap in digital infrastructure, such as internet access and information security. This limits the ability of digital transformation to create a tangible economic impact in the short term.

The impact also needs sufficient time to appear, as investment in government digitization is usually long-term, and its impact on growth appears years later by improving the efficiency of services, reducing costs, and stimulating investment. In general, the nature of African economies, which rely heavily on traditional sectors such as agriculture and natural resources, may weaken the direct role of digital readiness in stimulating growth.

Based on the findings of this study, policymakers should promote the adoption of artificial intelligence in African governments, which requires a multidimensional strategy. Strengthening governance through robust legal frameworks, institutional capacity building, and transparent digital strategies is essential to creating an enabling environment. Developing technology by supporting local innovation, digitizing public services, and investing in digital skills will also promote sustainable innovation. Equally important is effective data management, which includes building secure repositories, implementing open data policies, and improving data quality standards to ensure its reliability. Finally, widespread AI deployment will rely on improving infrastructure through broadband expansion, establishing local data centres, and enhancing cybersecurity.

This study opens several directions for future research on the relationship between government AI readiness and economic growth, particularly in developing regions. First, future studies may examine the long-term effects of AI preparedness by using longer time horizons or alternative dynamic modelling approaches that can better capture the delayed impact of technological adoption on economic performance. Since digital transformation often requires a considerable period before generating observable macroeconomic outcomes, longitudinal analyses may offer deeper insights into the actual economic benefits associated with artificial intelligence readiness. Furthermore, future research could integrate additional institutional and structural variables that may influence the relationship between AI readiness and economic growth. Variables such as human capital development, the quality of digital infrastructure, innovation capacity, research and development expenditure, and governance effectiveness may play a crucial role in transforming policy readiness into tangible economic productivity. Incorporating these factors could help clarify the mechanisms through which AI readiness contributes to economic growth.

Future studies may also benefit from adopting comparative or regional approaches. By comparing African economies with other developing regions, it is possible to obtain valuable evidence to determine whether the limited impact observed in this study is a result of structural characteristics specific to Africa or broader patterns across developing economies.

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The data used in this study are publicly available and can be accessed from the following sources: The Government AI Readiness Index provided by Oxford Insights, available at:
https://oxfordinsights.com/ai-readiness/government-ai-readiness-index-2025/
The World Bank database (https://data.worldbank.org/indicator/NY.GDP.MKTP.KD).
These sources provide open-access data used for analysis in this study.
Conflict of Interest
The author declares no conflict of interest.
AI Tools Statement
The author confirms that no AI tools were used in the preparation of this manuscript.
Author Contributions
The author is solely responsible for all aspects of this work.

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