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AI Readiness across Nations: A Panel Analysis of Policy, Governance, and Innovation Factors

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Abstract

This study analyzes the determinants of national AI readiness across 155 countries from 2020 to 2024 using fixed effects panel regression. Results show that human capital, data availability, infrastructure, and innovation capacity are the strongest predictors of AI readiness. Leadership vision, governance ethics, and adaptability also have significant positive effects. The findings offer evidence-based policy recommendations to build resilient and future-ready AI strategies.

Keywords: Artificial Intelligence Readiness, Human Capital, Digital Infrastructure, Governance and Ethics, Innovation Capacity

1. Introduction

Artificial Intelligence (AI) is transforming economies, public services, and global competition. As AI diffusion accelerates, the ability of countries to effectively adopt and integrate AI systems — their AI readiness — becomes a critical driver of future prosperity and governance success.

While early studies mainly emphasized technological infrastructure, recent research suggests that AI readiness is a multidimensional phenomenon, involving leadership vision, governance ethics, human capital, organizational adaptability, and the quality of data ecosystems. Yet, there remains limited comprehensive evidence identifying which factors matter most for building national AI readiness.

This study addresses this gap by using a large panel dataset covering 155 countries over 2020–2024 to systematically identify the key determinants of AI readiness. The findings aim to provide evidence-based guidance for governments to strengthen their AI preparedness for the coming decade.

2. Literature Review

2.1 Defining AI Readiness

AI readiness refers to a nation's capability to adopt, deploy, regulate, and benefit from artificial intelligence technologies (World Economic Forum, 2018; OECD, 2019). Traditionally measured through technological infrastructure, AI readiness is now increasingly viewed as a complex combination of technological, human, organizational, governance, and data factors (Bughin et al., 2018; Brynjolfsson & McAfee, 2014).

2.2 Determinants of AI Readiness

National AI readiness is shaped by a complex set of interrelated factors. Vision and leadership are crucial for setting strategic priorities and driving national commitment to AI development (Westerman et al., 2014). Effective governance and ethics frameworks, including data protection regulations, transparency measures, and responsible AI principles, enhance public trust, reduce adoption barriers, and promote responsible innovation (Floridi et al., 2018). Digital capacity, reflected in robust ICT infrastructure and widespread digital penetration, forms the essential foundation for AI systems deployment (Brynjolfsson

& McAfee, 2014). Adaptability, both institutional and workforce-related, enables countries to respond quickly and flexibly to technological change, facilitating the smooth integration of AI technologies (Davenport & Ronanki, 2018).

Human capital, particularly the availability of skilled labor in STEM fields, underpins the development, adoption, and sustainability of AI ecosystems (Arntz, Gregory, & Zierahn, 2016). A strong innovation ecosystem, characterized by research, entrepreneurship, and venture capital availability, fosters the experimentation necessary for AI advancement (Porter & Heppelmann, 2014). Beyond digital infrastructure, reliable physical infrastructure—including broadband access and stable energy supplies—is also vital to support AI systems (OECD, 2019). The strength of a country's data ecosystem, in terms of both data availability and data representativeness, critically affects the quality, fairness, and scalability of AI models (Barocas, Hardt, & Narayanan, 2019; Mehrabi et al., 2021). Finally, country size, whether measured by GDP or population, influences AI readiness through economies of scale, though larger countries may also face greater bureaucratic and coordination challenges (Acemoglu & Restrepo, 2019).

2.3 Research Gap

Although AI readiness has become an increasingly important topic, most existing studies remain limited in several ways. First, prior research often focuses narrowly on technological factors such as digital infrastructure or innovation capacity, overlooking the broader role of governance frameworks, human capital, and data ecosystems (e.g., Westerman et al., 2014; Davenport and Ronanki, 2018). Second, much of the literature relies on cross-sectional designs, offering only a static view of AI readiness at a single point in time rather than capturing its evolution and dynamics (Brynjolfsson and McAfee, 2014; Arntz, Gregory, and Zierahn, 2016). Third, few studies have simultaneously integrated multiple pillars—technological, human, governance, infrastructure, and data dimensions—into a unified empirical framework. Additionally, existing analyses rarely leverage large, recent, global panel datasets that can support more robust causal inferences.

Moreover, many prior works stop at diagnostic assessments without offering direct, practical policy recommendations for improving national AI capabilities (Floridi et al., 2018). This study addresses these gaps by building a comprehensive model that combines all major drivers of AI readiness, using newly available longitudinal data across 155 countries from 2020 to 2024, and applying fixed-effects panel econometric techniques to control for unobserved heterogeneity and time-specific shocks. In doing so, it provides not only a deeper theoretical understanding of AI readiness but also actionable insights for governments seeking to enhance their national strategies.

3. Research Contribution

This study offers several important contributions to the understanding of national AI readiness. First, it develops a comprehensive framework by testing multiple national-level drivers of AI readiness within a unified empirical model, rather than examining isolated factors independently. Second, it leverages the newest available data, drawing on a balanced panel dataset covering 155 countries from 2020 to 2024, which allows for dynamic, longitudinal analysis rather than relying on static cross-sectional snapshots. Third, the study provides direct policy relevance, offering clear and practical guidance for governments seeking to strengthen their AI strategies and investments based on empirically validated drivers of success. Finally, this research introduces a pioneering model that is among the first to isolate and quantify the longitudinal effects of national capabilities—such as digital capacity, governance quality, human capital, and data infrastructure—on AI readiness, thus filling a critical gap in the existing literature.

4. Methodology

4.1 Research Design

The study applies fixed effects panel regression to control for country-specific unobserved heterogeneity and year-specific shocks. This design leverages within-country changes over time rather than cross-country comparisons alone.

4.2 Data Description and Variable Construction

This study employs panel data from 155 countries observed annually between 2020 and 2024. The primary source is the *Government AI Readiness Index*, produced by Oxford Insights (Fuentes Nettel et al., 2024). The dependent variable, AI Readiness Score, reflects a country's overall capability to adopt, deploy, and govern artificial intelligence technologies. It is a composite score aggregating performance across three core pillars: Government, Technology Sector, and Data & Infrastructure.

Independent variables are constructed from detailed dimensions provided by Oxford Insights. These dimensions capture critical aspects such as national leadership vision for AI, governance ethics, public sector digital capacity, innovation environment, human capital, and the strength of national data ecosystems. Each dimension includes specific indicators sourced from reputable international datasets, ensuring methodological consistency. All variables are standardized on a yearly basis to allow for comparability across countries and over time. Table 1 summarizes the dimensions, indicators, and primary data sources used to operationalize AI readiness determinants for this study. All variables are standardized yearly.

Table 1: Dimensions, Indicators, and Sources for Measuring National AI Readiness (Oxford Insights, 2020–2024)

Pillar	Dimension	Description	Indicator(s)	Primary Source
Government	Vision	Existence of national AI strategy.	National AI Strategy (0/50/100)	OECD AI Policy Observatory, UN IDIR AI Policy Portal
	Governance and Ethics	Regulations and ethical frameworks for trustworthy AI.	Data Protection Laws, Cybersecurity Index, Regulatory Quality, Ethical AI Principles, Accountability	GovTech Maturity Index, IAPP Global Privacy Directory, ITU, World Bank Governance Indicators, Desk Research
	Digital Capacity	Internal digital infrastructure and public sector AI skills.	Online Services, Foundational IT Infrastructure, Government Support for AI Adoption, Public Sector AI Skills	UN E-Government Survey, GovTech Maturity Index, World Economic Forum Executive Opinion Survey, Global Index on Responsible AI

	Adaptability	Ability of government to innovate and respond to change.	Government Effectiveness, Responsiveness to Change, Procurement Data Transparency	World Bank Governance Indicators, World Economic Forum Executive Opinion Survey, Global Data Barometer
Technology Sector	Maturity	Capability of the tech sector to deliver AI solutions.	AI Unicorns, Non-AI Tech Unicorns, ICT Goods/Services Trade, Computer Software Spending	CB Insights, UNCTAD, Global Innovation Index
	Innovation Capacity	Strength of national innovation environment.	Time Dealing with Regulation, VC Availability, R&D Spending, Adoption of AI for Innovation, AI Research Output	World Bank WDI, DealRoom, UNESCO, World Economic Forum Executive Opinion Survey, Scimago
	Human Capital	Availability of workforce skills relevant to AI.	STEM Graduates, Female STEM Graduates, GitHub Users per Capita, Engineering and Technology Education Quality, ICT Skills	UNESCO, GitHub Innovation Graph, QS Rankings, Network Readiness Index
Data and Infrastructure	Infrastructure	Quality of telecom and digital infrastructure.	Telecom Infrastructure Index, Supercomputers, Broadband Quality, 5G Readiness, Key Technologies Adoption	UN E-Government Survey, Top500, EIU Inclusive Internet Index, GSMA Mobile Connectivity Index, World Economic Forum Executive Opinion Survey
	Data Availability	Access to open and reliable datasets.	Open Data, Data Governance, Mobile Subscriptions, Internet Access, Statistical Capacity	Global Data Barometer, ITU, World Bank SPI GitHub Report
	Data Representativeness	Inclusiveness and fairness of	Gender Gap in Internet Access,	GSMA Mobile Connectivity Index,

		national data ecosystems.	Mobile Device Affordability	EIU Inclusive Internet Index

4.3 Variables

The dependent variable in this study is AI Readiness (Overallscore), which measures each country's overall preparedness to adopt and implement artificial intelligence technologies, based on the composite score from the Oxford Insights Government AI Readiness Index. The independent variables include a set of national capability factors: Vision (national AI strategy presence), Governance and Ethics (quality of AI-related governance), Digital Capacity (government's internal digital infrastructure and services), Adaptability (institutional flexibility to adopt new technologies), Innovation Capacity (national environment for R&D and AI innovation), Human Capital (availability of STEM skills and AI expertise), Infrastructure (telecom and digital infrastructure), Data Representativeness (fairness and inclusiveness of national datasets), and Data Availability (accessibility of open and reliable datasets). Size, measured by GDP or population, is included both as an independent variable and as a control variable to account for country scale effects. Additionally, year effects are controlled for to capture unobserved global shocks or annual variations in AI readiness during the 2020–2024 period.

Table 2: Summary of Variables

Variable Type	**Variable Name**	**Description**
Dependent Variable	AI Readiness (Overallscore)	Composite score of national AI readiness from Oxford Insights
Independent Variables	Vision	Existence and quality of national AI strategy
	GovtandEthics	Governance frameworks, ethical AI policies, data protection laws
	DigitalCapacity	Digital infrastructure, online services, government AI capabilities
	Adaptability	Government effectiveness and responsiveness to technological change
	InnovationCapacity	R&D spending, startup environment, adoption of AI innovations
	HumanCapital	STEM education levels, AI-skilled workforce availability
	Infrastructure	Telecommunications, broadband, supercomputing, 5G readiness
	DataRepresentativeness	Fairness and inclusiveness of national data sources
	DataAvailability	Accessibility and quality of national datasets
	Size	Country size, measured by GDP or population
Control Variables	Size	Controls for the effect of national scale
	Year effects	Controls for time-specific shocks or trends (2020–2024)

4.4 Analytical Strategy

This study begins with a descriptive analysis of the dataset, providing an overview of the distributions of key variables and presenting a correlation matrix to explore the relationships between them. To estimate the determinants of national AI readiness, a fixed effects panel regression model is employed. This approach controls for unobserved, time-invariant country-specific factors, focusing on within-country variation over the 2020–2024 period. Cluster-robust standard errors are used to adjust for potential serial correlation and heteroskedasticity within countries, ensuring more reliable inference. Year fixed effects are included to control for global shocks, policy shifts, or macroeconomic changes that may have affected AI readiness trends across all countries simultaneously during the study period. This methodology provides a robust framework for identifying the key factors influencing national AI readiness over time.

4.5 Model Specification

The empirical model used to estimate the determinants of national AI readiness is specified as follows:

$$\begin{aligned} AI\ readiness_{ct}\ \beta_0 &+ \beta_1 Vision_{ct} + \beta_2 GovtEthics_{ct} + \beta_3 DigitalCapacity_{ct} \\ &+ \beta_4 Adaptibility_{ct}\ \beta_5 Size_{ct} + \beta_6 InnoionCapacity_{ct} + \beta_7 Human\ Capital_{ct} \\ &+ \beta_8 Infrastructure_{ct} + \beta_9 DataRepresentativeness_{ct} + \beta_{10} DataAvailability_{ct} \\ &+ \mu_c + \lambda_t + \epsilon_{ct} \end{aligned}$$

where c indexes countries and t indexes years (2020–2024). μ_c *captures unobserved, time-invariant country-specific fixed effects,* λ_t*controls for year-specific shocks or macroeconomic factors affecting all countries, and* ϵ_{ct} *is the idiosyncratic error term.*

This specification follows standard fixed-effects panel regression practices, commonly used to control for heterogeneity across countries and remove bias from time-invariant omitted variables (Wooldridge, 2010). Fixed effects allow the analysis to focus on within-country variation over time, isolating how changes in national capabilities—such as digital capacity, governance frameworks, or innovation environment—relate to changes in AI readiness. Cluster-robust standard errors are employed to adjust for potential serial correlation and heteroskedasticity within countries, improving inference reliability (Arellano, 1987). The inclusion of year fixed effects addresses possible global events—such as advances in AI technology or major international policy developments—that could systematically influence all countries' AI readiness scores in a given year. This model design is consistent with prior cross-country studies analyzing institutional readiness, digital adoption, and governance effects (e.g., Acemoglu & Restrepo, 2019; Arntz, Gregory, & Zierahn, 2016).

5. Results

5.1 Descriptive Statistics

Table 3 presents the descriptive statistics for the key variables in the dataset (n=775). The Overall Score has a mean of 47.66 with a standard deviation of 16.70, indicating moderate performance with considerable variability among observations. Vision displays a wide spread, with a mean of 40.26 but a very high standard deviation (46.78), suggesting large differences across cases, including instances scoring zero.

Government and Ethics, Digital Capacity, and Adaptability have similar average scores (approximately 50), with moderate dispersion (standard deviations between 15 and 20). The Size variable, representing organizational size or capacity, averages 22.25 but varies significantly (std. dev. 14.06), ranging from very small to much larger entities.

Innovation Capacity and Human Capital show mean values of 43.44 and 39.56, respectively, with relatively high variability, pointing to uneven strengths across units. Infrastructure also shows significant dispersion, while Data Availability and Data Representativeness score higher on average (means of 60.39 and 72.07 respectively), indicating better performance in data-related dimensions. However, both still exhibit substantial variation across observations, especially Data Representativeness, which ranges from as low as 1.37 to full coverage at 100.

Overall, the data suggest significant heterogeneity across the sample in terms of capacities, infrastructure, and digital and ethical governance attributes.

Table 3: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
S No	775	388.00	223.87	1	775
Overall Score	775	47.66	16.70	13.46	88.16
Vision	775	40.26	46.78	0	100
Government and Ethics	775	52.86	20.11	1.73	97.38
Digital Capacity	775	51.64	17.35	11.46	93.82
Adaptability	775	49.99	15.65	5.64	93.98
Size	775	22.25	14.06	0.70	87.04
Innovation Capacity	775	43.44	15.20	0	93.02
Human Capital	775	39.56	15.70	5.70	80.39
Infrastructure	775	45.27	21.02	5.57	93.77
Data Availability	775	60.39	19.79	15.14	98.70
Data Representativeness	775	72.07	16.58	1.37	100

5.2 Regression Results

The fixed effects panel regression results, using AI Readiness (Overallscore) as the dependent variable, are summarized below:

Table 4: Descriptive Statistics

Variable	Coefficient	Std. Error	t-Statistic	p-Value	95% Confidence Interval
Vision	0.0837	0.0010	86.63	0.000	[0.0818, 0.0855]
Govt and Ethics	0.0957	0.0028	34.52	0.000	[0.0903, 0.1012]
Digital Capacity	0.0740	0.0034	21.95	0.000	[0.0674, 0.0806]
Adaptability	0.0822	0.0033	24.80	0.000	[0.0757, 0.0887]
Size	0.1305	0.0046	28.36	0.000	[0.1214, 0.1395]
Innovation Capacity	0.1064	0.0039	27.56	0.000	[0.0988, 0.1140]
Human Capital	0.1249	0.0041	30.60	0.000	[0.1169, 0.1329]
Infrastructure	0.1158	0.0030	38.61	0.000	[0.1099, 0.1216]
Data Representativeness	0.0623	0.0025	25.04	0.000	[0.0574, 0.0672]
Data Availability	0.1233	0.0031	40.26	0.000	[0.1173, 0.1293]
Constant	1.6544	0.1759	9.40	0.000	[1.3090, 1.9998]

5.3 Multicollinearity Diagnostics

To ensure that multicollinearity does not bias the regression estimates, Variance Inflation Factors (VIFs) were calculated for all independent variables. Table X presents the VIF values for each predictor in the model.

Table 5. Variance Inflation Factors (VIFs)

Variable	VIF	1/VIF
Size	4.54	0.220
Human Capital	4.46	0.224
Infrastructure	4.32	0.232
Data Availability	3.99	0.251
Innovation Capacity	3.74	0.267
Digital Capacity	3.71	0.269
Governance and Ethics	3.38	0.296
Adaptability	2.92	0.342
Vision	2.22	0.451
Data Representativeness	1.85	0.540
Mean VIF	3.51	

The VIF values range from 1.85 (Data Representativeness) to 4.54 (Size), with a mean VIF of 3.51. All VIFs are well below the common thresholds of 5 or 10 typically used to flag problematic multicollinearity (O'Brien, 2007). This suggests that multicollinearity is not a serious concern in the dataset. The moderate VIFs observed for Size, Human Capital, and Infrastructure are expected, given that larger countries often have better educational systems and more developed digital infrastructure. However, their VIF values are still within acceptable limits, and no corrective action—such as dropping variables or applying principal component analysis—is necessary. Therefore, the fixed effects regression results can be interpreted with confidence that multicollinearity does not distort the estimated coefficients.

5.4 Interpretation of Key Results

The analysis reveals that **leadership vision** ($\beta = 0.0837$, $p < 0.001$) is a significant driver of national AI readiness. Countries with a strong, strategic agenda for AI are more likely to implement coordinated efforts toward AI integration. Clear leadership not only sets priorities but also mobilizes resources and aligns stakeholders.

Governance and ethical frameworks ($\beta = 0.0957$, $p < 0.001$) also have a substantial positive effect. Transparent, trustworthy institutions help create regulatory certainty and public confidence in AI systems. These elements are essential for encouraging responsible innovation and adoption.

Although **digital capacity** ($\beta = 0.0740$, $p < 0.001$) remains a critical enabler, its effect is somewhat smaller compared to governance and human capital. This suggests that infrastructure alone is insufficient without complementary institutional and human support. Similarly, **institutional adaptability** ($\beta = 0.0822$, $p < 0.001$) plays a key role, allowing countries to respond rapidly to evolving technologies and policy challenges.

Among the strongest predictors is **human capital** ($\beta = 0.1249$, $p < 0.001$), underscoring the importance of a well-educated workforce, particularly with STEM expertise. Nations with greater investments in edu-

cation and training are better positioned to develop, manage, and regulate AI technologies.
Infrastructure ($\beta = 0.1158$, $p < 0.001$), both physical and digital, supports widespread AI deployment across sectors. Meanwhile, **innovation capacity** ($\beta = 0.1064$, $p < 0.001$) reflects a country's ability to absorb and advance AI technologies through dynamic research and development ecosystems.
Within the **data ecosystem**, two factors stand out. **Data representativeness** ($\beta = 0.0623$, $p < 0.001$) ensures inclusivity and reduces bias, while **data availability** ($\beta = 0.1233$, $p < 0.001$) provides the foundation for training and deploying effective AI systems. The strength of the latter's effect highlights the importance of accessible, high-quality data.
Finally, **country size** ($\beta = 0.1305$, $p < 0.001$) appears to confer structural advantages such as resource scale and institutional depth. However, size alone does not guarantee AI readiness in the absence of effective leadership and governance mechanisms.

5.5 Comparative Analysis of AI Readiness Determinants

The regression analysis confirms that all independent variables are statistically significant at the 1% level ($p < 0.01$), indicating robust positive relationships with national AI readiness. Among the various determinants, **country size** ($\beta = 0.1305$), **human capital** ($\beta = 0.1249$), and **data availability** ($\beta = 0.1233$) exhibit the largest marginal effects. These findings suggest that structural scale, a well-educated and technically skilled workforce, and open access to large, high-quality datasets are the most critical components for enhancing national AI capabilities. In particular, investments in STEM education and the development of technical skills should be central to national AI strategies, alongside initiatives to improve the accessibility and usability of data resources.
The next tier of influential variables includes **infrastructure** ($\beta = 0.1158$) and **innovation capacity** ($\beta = 0.1064$). These factors underscore the importance of physical and digital infrastructure—such as broadband networks, cloud computing, and supercomputing facilities—as well as environments that support research and development. Together, they represent essential building blocks for AI experimentation, deployment, and scaling.
Governance and ethics ($\beta = 0.0957$) and **leadership vision** ($\beta = 0.0837$) also make substantial contributions. Their positive effects highlight the value of clear strategic direction and the presence of ethical, transparent governance frameworks in boosting AI readiness. These institutional elements not only support responsible AI adoption but also foster public trust and regulatory certainty.
While still significant, **digital capacity** ($\beta = 0.0740$), **institutional adaptability** ($\beta = 0.0822$), and **data representativeness** ($\beta = 0.0623$) show comparatively smaller coefficients. This indicates that although digital service delivery, government responsiveness, and equitable data inclusion play supportive roles, they are relatively less influential than the core drivers mentioned above.
In summary, the findings point to a strategic policy hierarchy. To maximize national AI readiness, governments should prioritize (1) the development of human capital, (2) the expansion of data access and quality, (3) investment in infrastructure and innovation ecosystems, and (4) the establishment of strong governance and a coherent national AI vision. Secondary efforts should aim to enhance adaptability, improve digital service capabilities, and ensure inclusive, representative data practices.

6. Policy Recommendations

Based on the regression results, several actionable policy priorities emerge for governments seeking to enhance their national AI readiness.

First, investment in human capital must be a top priority. The significant positive coefficient for Human Capital (0.1249) highlights that countries with better STEM education systems, stronger AI skill development programs, and greater technical workforce capabilities achieve higher AI readiness scores. Governments should prioritize reforms that expand access to advanced STEM education, incentivize AI-specific training programs, and foster university-industry collaboration to ensure graduates have practical AI and data science skills.

Second, improving data availability is crucial. The strong effect of Data Availability (0.1233) suggests that countries with open, accessible, and high-quality datasets are better positioned to deploy AI technologies. Policymakers should invest in building robust open data portals, enforce data governance frameworks that protect privacy while enabling research and innovation, and promote interoperability standards across sectors.

Third, developing digital and physical infrastructure should be accelerated. The high coefficient for Infrastructure (0.1158) emphasizes that reliable internet connectivity, 5G rollout, cloud computing infrastructure, and supercomputing capabilities are foundational for AI growth. Public-private partnerships can be leveraged to expand broadband access, especially in rural or underserved areas, and to ensure that infrastructure keeps pace with emerging technological demands.

Fourth, fostering innovation ecosystems is essential. The positive impact of Innovation Capacity (0.1064) shows that national R&D spending, venture capital availability, and startup support are directly linked to AI readiness. Governments should introduce targeted funding for AI research, reduce regulatory barriers for startups, and create AI-focused innovation hubs or technology parks.

Fifth, governance and strategic vision remain important complementary factors. The statistically significant effects of Governance and Ethics (0.0957) and Vision (0.0837) underline the necessity of coherent national AI strategies and ethical AI governance. Countries should ensure that AI strategies are not only aspirational but operationalized with specific policy roadmaps. Furthermore, establishing clear ethical frameworks aligned with international standards (e.g., OECD AI Principles) will help build public trust in AI systems.

Finally, while Digital Capacity, Adaptability, and Data Representativeness have slightly smaller coefficients, they should not be overlooked. Continuous efforts to digitize public services, improve governmental responsiveness to technological change, and ensure that data ecosystems are inclusive and representative of all societal groups will sustain long-term AI readiness.

In summary, governments aiming to boost AI readiness should prioritize human capital development, data availability, infrastructure expansion, innovation promotion

7. Conclusion

This study provides one of the first large-scale, longitudinal analyses of the determinants of national AI readiness across 155 countries over the period 2020–2024.

Using fixed effects panel regression, the results highlight that AI readiness is shaped not just by technological infrastructure but also by leadership vision, governance ethics, human capital, adaptability, and the strength of national data ecosystems.

Human-centered factors — such as education, governance quality, and visionary leadership — emerge as even stronger predictors of AI readiness than digital infrastructure alone.

This underscores a critical lesson for policymakers: technological investment without parallel investment in people, ethics, and governance will not be sufficient to secure AI leadership in the coming decade.

By offering clear, evidence-based policy recommendations, this study aims to support governments globally in building resilient, ethical, and innovative AI ecosystems — helping nations not only adopt AI but do so in ways that are inclusive, sustainable, and future-ready.

References

1. Acemoglu, Daron, and Pascual Restrepo. *The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand*. Cambridge, MA: National Bureau of Economic Research, 2019.
2. Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." OECD Social, Employment and Migration Working Papers, no. 189, 2016.
3. Barocas, Solon, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. 2019. [Manuscript].
4. Brynjolfsson, Erik, and Andrew McAfee. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton & Company, 2014.
5. Davenport, Thomas H., and Rajeev Ronanki. "Artificial Intelligence for the Real World." *Harvard Business Review* 96, no. 1 (2018): 108–116.
6. Floridi, Luciano, Josh Cowls, Monica Beltrametti, et al. "AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations." *Minds and Machines* 28, no. 4 (2018): 689–707.
7. Mehrabi, Ninareh, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. "A Survey on Bias and Fairness in Machine Learning." *ACM Computing Surveys* 54, no. 6 (2021): 1–35.
8. OECD. *Artificial Intelligence in Society*. Paris: OECD Publishing, 2019.
9. Oxford Insights. *Government AI Readiness Index 2024*. Oxford: Oxford Insights, 2024.
10. Porter, Michael E., and James E. Heppelmann. "How Smart, Connected Products Are Transforming Competition." *Harvard Business Review* 92, no. 11 (2014): 64–88.
11. Westerman, George, Didier Bonnet, and Andrew McAfee. *Leading Digital: Turning Technology into Business Transformation*. Boston: Harvard Business Review Press, 2014.
12. Wooldridge, Jeffrey M. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press, 2010.
13. Arellano, Manuel. "Computing Robust Standard Errors for Within-Groups Estimators." *Oxford Bulletin of Economics and Statistics* 49, no. 4 (1987): 431–434.
14. World Economic Forum. *Readiness for the Future of Production Report 2018*. Geneva: World Economic Forum, 2018.