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AI Investment Potential Index:

Mapping Global Opportunities for Sustainable Development

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AI Investment Potential Index

Mapping Global Opportunities for Sustainable Development

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Abstract

This paper examines the potential of artificial intelligence (AI) investment to drive sustainable development across diverse national contexts. By evaluating critical factors, including AI readiness, social inclusion, human capital, and macroeconomic conditions, we construct a nuanced and comprehensive analysis of the global AI landscape. Employing advanced statistical techniques and machine learning algorithms, we identify nations with significant untapped potential for AI investment.

We introduce the AI Investment Potential Index (AIIPI), a novel instrument designed to guide financial institutions, development banks, and governments in making informed, strategic AI investment decisions. The AIIPI synthesizes metrics of AI readiness with socio-economic indicators to identify and highlight opportunities for fostering inclusive and sustainable growth.

The methodological novelty lies in the weight selection process, which combines statistical modeling and also an entropy-based weighting approach. Furthermore, we provide detailed policy implications to support stakeholders in making targeted investments aimed at reducing disparities and advancing equitable technological development.

Keywords

AI Investment Potential Index, sustainable development, artificial intelligence, investment decisions, equitable growth, AI readiness.

JEL codes

O33	Technological Change Choices and Consequences Diffusion Processes
F63	Economic Development
C43	Index Numbers and Aggregation
G11	Portfolio Choice Investment Decisions
Q01	Sustainable Development

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Résumé

Cet article examine le potentiel d' investissement en intelligence artificielle (IA) pour stimuler le développement durable dans divers contextes nationaux. En évaluant des facteurs clés tels que l'état de préparation à l'IA, l'inclusion sociale, le capital humain et les conditions macroéconomiques, nous élaborons une analyse nuancée et complète du paysage mondial de l'IA.

À l'aide de techniques statistiques avancées et d'algorithmes d'apprentissage automatique, nous identifions les pays présentant un potentiel inexploité significatif pour les investissements en IA. Nous introduisons l'Indice de Potentiel d'Investissement en Intelligence Artificielle (AIIPI), un outil novateur conçu pour orienter les institutions financières, les banques de développement et les gouvernements dans leurs décisions d'investissement stratégique en IA.

L'AIIPI combine des indicateurs de préparation des pays à l'IA et des données socio-économiques pour identifier des opportunités de croissance inclusive et durable, en analysant des facteurs clés tels que les infrastructures numériques, le développement technologique, l'ouverture à l'IA, la stabilité politique et l'attractivité économique. L'innovation méthodologique de cet indice réside dans le processus de sélection des pondérations, qui combine une modélisation statistique et une approche de pondération basée sur l'entropie. Enfin, nous proposons des recommandations détaillées en matière de politique publique pour accompagner les parties prenantes dans la réalisation d'investissements ciblés, visant à réduire les disparités et à promouvoir un développement technologique inclusif et durable.

Mots-clés

Indice du Potentiel d'Investissement en IA, développement durable, intelligence artificielle, décisions d'investissement, croissance équitable, état de préparation à l'IA.

1. Introduction

As we reach the midpoint of the 2030 Agenda for Sustainable Development, initially established to achieve the Sustainable Development Goals (SDGs), the global community confronts a daunting reality: progress has significantly lagged behind expectations. Currently, only 17% of the SDGs are on track, with nearly half (48%) facing considerable delays, and more than a third (35%) either stagnating or regressing compared to their 2015 baselines (United Nations Statistics Division, 2024). This troubling scenario results from a complex interplay of factors, including climate change, geopolitical tensions, and global health crises, which have collectively undermined international cooperation and impeded progress (United Nations Environment Programme, 2023; Le *et al.*, 2022; Kharas, 2021).

Amid these challenges, the rapid evolution of artificial intelligence (AI) presents both a remarkable opportunity and a formidable challenge. Generative AI technologies such as ChatGPT, Copilot, Gemini, and Claude exemplify AI's potential to transform economic, social, and environmental systems. Defined by the Organisation for Economic Co-operation and Development (OECD) as "a machine-based system that, for explicit or implicit objectives, infers from its inputs how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" (OECD, 2024). AI is already driving substantial changes across industries. For example, AI is optimizing energy management, enhancing the efficiency of renewable resources, personalizing education to address learning gaps, and revolutionizing healthcare diagnostics and prognostics (Addo *et al.*, 2021; Nahar, 2024; Willige, 2024).

From an economic perspective, the impact of AI remains uncertain, with projected contributions from generative AI ranging from as low as 0.5% of global GDP over the next decade (Acemoglu, 2024) to as high as 7%, or $7 trillion (Goldman Sachs, 2023). Such varying estimates reflect the current ambiguity surrounding AI's aggregate economic impact, whether through recognized gains in existing industries or anticipated future benefits across broader economic activities.

However, the potential benefits of AI are unevenly distributed. To fully harness AI for sustainable development, substantial investments are necessary, particularly in developing countries, where access to technology, financing, and skilled labor remains limited. This disparity raises critical questions about the capacity of these nations to engage with and benefit from the AI revolution. For instance, in Africa, funding remains a significant barrier for AI start-ups and research initiatives such as Masakhane, which focuses on natural language processing (NLP) research in African languages (Madu *et al.*, 2024). These initiatives require substantial investments in cloud computing, skilled personnel, and computational infrastructure to succeed.

Recognizing AI's transformative potential, various development organizations are increasingly focusing on strategic investments to address pressing social and environmental challenges. The AI for Development (AI4D) program, launched at the UK AI Safety Summit in November 2023, exemplifies this commitment through a collaborative initiative involving the International Development Research Centre (IDRC), the Foreign, Commonwealth and Development Office (FCDO), the Bill and Melinda Gates Foundation (BMGF), and the United States Agency for International Development (USAID). With CAD 130 million committed over five years, AI4D aims to leverage AI to reduce inequalities and strengthen health, education, and food systems while enhancing resilience to climate change (International Development Research Centre, 2023). Similarly, initiatives like the Agence Française de Développement (AFD) [AI challenge for marine biodiversity] reflect the growing interest in AI's role in achieving the SDGs.

In this context, understanding how and where to invest in AI becomes essential for fostering inclusive and sustainable growth. This paper introduces the AI Investment Potential Index (AIIPI), a novel tool designed to guide development financial institutions, banks, and governments in making informed decisions about AI investments. By integrating AI readiness indicators, social inclusion metrics, and macroeconomic outlooks, the AIIPI framework provides a multi-faceted assessment of the global AI landscape, effectively identifying countries with substantial untapped investment potential. Through a combination of statistical techniques and advanced machine learning algorithms, this research uncovers latent patterns of similarity among countries, thereby highlighting strategic opportunities for investments aimed at bridging current technological gaps and fostering equitable growth in AI capabilities.

This paper is structured as follows: Section 2 provides a review of the relevant literature, Section 3 outlines the data and methodology used, Section 4 presents the analysis and key findings, and Section 5 discusses the insights and policy implications.

2. Literature Review

Artificial Intelligence (AI) has emerged as a transformative force with the potential to fundamentally reshape global economies and drive sustainable development. The rapid advancements in AI technologies, coupled with increasing investments, underscore its growing significance in driving economic growth and social progress. This literature review examines the key factors influencing AI adoption and its implications for sustainable development, emphasizing the diverse challenges and opportunities across different countries.

The Economic Impact of AI

AI's potential to reshape the global economy has frequently been likened to a new industrial revolution. McKinsey estimates that generative AI alone could contribute between $2.6 trillion and $4.4 trillion to global productivity—an amount roughly equivalent to the entire GDP of the United Kingdom (Chui *et al.*, 2023). However, AI's impact is not uniform across different economies. The current focus on automating repetitive tasks suggests that while AI's contribution to productivity could be significant, its broader macroeconomic effects may remain moderate, resulting in an increase in Total Factor Productivity (TFP) of only 0.55% to 0.71% (Acemoglu, 2024). TFP, a measure of economic efficiency, reflects how effectively labor and capital are utilized, incorporating factors such as technology, innovation, and workforce skills.

Digitalization and AI's Role in Sustainable Development

The digital economy is increasingly integral to global economic dynamics, contributing 15.5% of global GDP in 2023 (Al Yahya, 2023). AI is expected to be a key driver of this growth, with more than two-thirds of new value projected to arise from digitally enabled platforms over the next decade (World Economic Forum, 2024). The private sector's enthusiasm for AI investment largely stems from its potential to enhance productivity and drive economic expansion.

AI's contribution to the United Nations' Sustainable Development Goals (SDGs) is also significant, with potential impacts—both positive and negative—on 134 out of 169 SDG targets (Vinuesa, 2020). AI can advance goals related to Industry, Innovation, and Infrastructure (SDG 9), Reduced Inequalities (SDG 10), Peace, Justice, and Strong Institutions (SDG 16), and Partnerships for the Goals (SDG 17). However, these opportunities come with substantial risks.

For example, while AI-driven data analysis can enhance governance transparency and accountability, it may also exacerbate inequalities if implemented without sufficient attention to inclusivity (Nahar, 2024).

The United Nations has already launched over 408 AI-related projects across all 17 SDGs, highlighting the global commitment to leveraging AI for sustainable development (International Telecommunication Union, 2023). Nonetheless, the effective realization of AI's potential requires a nuanced understanding of its applications and the socio-economic contexts in which it is deployed.

Key Factors Influencing AI Adoption

AI adoption is *a priori* influenced by several critical factors, including digital infrastructure, technological sector development, government openness to AI, and political stability. These factors vary widely across countries, shaping the readiness and attractiveness of AI investments. In this research, we will test the statistical significance of these families of variables, and build our index based on these estimates. We will use the number of AI investments as a proxy of AI adoption in any particular country.

Digital Infrastructure: Robust digital infrastructure may be necessary to unlock AI's potential. This includes reliable hardware, cloud computing capabilities, high-speed broadband, and access to quality data (Oxford Insights, 2023). Many developing regions face significant infrastructural deficits, contributing to a persistent global digital divide. With over 2.6 billion people lacking internet access, particularly in regions such as Sub-Saharan Africa, disparities within and between countries continue to impede equitable AI adoption (United Nations, 2024). Addressing these gaps through targeted investments in digital infrastructure is therefore essential for inclusive AI growth.

Technological Sector Development: A well-developed technological sector, supported by a skilled workforce, could also be crucial for AI advancement. High-income countries, particularly the United States and China, lead in AI development due to substantial investments, vibrant AI ecosystems, and skilled labor. In 2020, US venture capital accounted for 43% of global AI investments, followed by China with 20% (OECD, n.d.). These nations have established themselves as leaders in AI research and commercialization, while many developing countries continue to face significant shortages of AI expertise (Khanal *et al.*, 2024). There are, however, exceptions, such as Malaysia and the some of the BRICS[2] countries (Brazil, Russia, India and China), which have made notable progress in AI research and education (Oxford Insights, 2023). Building a skilled workforce and fostering a supportive policy environment are essential for countries aspiring to develop a responsible AI ecosystem.

Government Openness to AI: Government support and regulation may also influence AI adoption. Effective regulatory frameworks can help mitigate risks associated with AI, such as bias, discrimination, and privacy violations (Fraisl *et al.*, 2024). The AI Government Readiness Index by Oxford Insights (2023) ranks countries based on their AI strategies, regulatory environments, and digital capacities. Strategic policies have enabled Singapore, for example, to position itself as a global leader in AI readiness despite its small geographic size (Khanal *et al.*, 2024). Development practitioners could therefore support governments in formulating AI strategies, implementing ethical frameworks, and strengthening digital capacities to foster responsible AI ecosystems.

Political Stability and AI Investments: Political stability and economic attractiveness are likely determinants of AI investment decisions. A stable political climate attracts and retains investments, talent, and businesses, facilitating AI development. Key indicators such as Foreign Direct Investment (FDI), government effectiveness, and corruption control are critical to a country's investment climate (Kaufmann & Kraay, 2023). Conversely, political instability can deter investments and foster irresponsible AI applications, leading to adverse effects such as misinformation and harmful content proliferation.

The existing literature underscores the importance of aligning AI investments with a country's stage of development. While advanced economies should focus on AI innovation and regulatory frameworks to maximize benefits, emerging and developing economies must prioritize foundational infrastructure and skill development. This study introduces the AI Investment Potential Index (AIIPI) as a novel tool to guide investment decisions, emphasizing the need for targeted investments to bridge existing gaps and promote inclusive, sustainable growth. By offering a comprehensive understanding of the global AI landscape, this research provides a roadmap for leveraging AI's potential to drive global progress.

[2] BRICS is an intergovernmental organization that aims to increase the economic and political influence of its member countries. BRICS initial membership consists of Brazil, Russia, India, China, and South Africa. In 2024, Saudi Arabia, Iran, Ethiopia, the United Arab Emirates, and Egypt joined BRICS.

3. Data and Methodology

The AI Investment Potential Index (AIIPI) framework is constructed using a comprehensive range of indicators derived from publicly available datasets such as those provided by the World Bank, Oxford Insights, GSMA, and Commission nationale de l'informatique et des libertés (CNIL). These datasets encapsulate multiple facets of AI investment potential, encompassing governance, infrastructure, human capital, economic environment, and digital capacity. A detailed enumeration of the variables, including descriptions and data sources, is available in Annex 1.

Exploratory data analysis, including descriptive statistics and assessment of missing values, was conducted to refine the dataset. Variables with extensive missing data were excluded, while highly correlated variables were consolidated to reduce redundancy (see Figure 1).

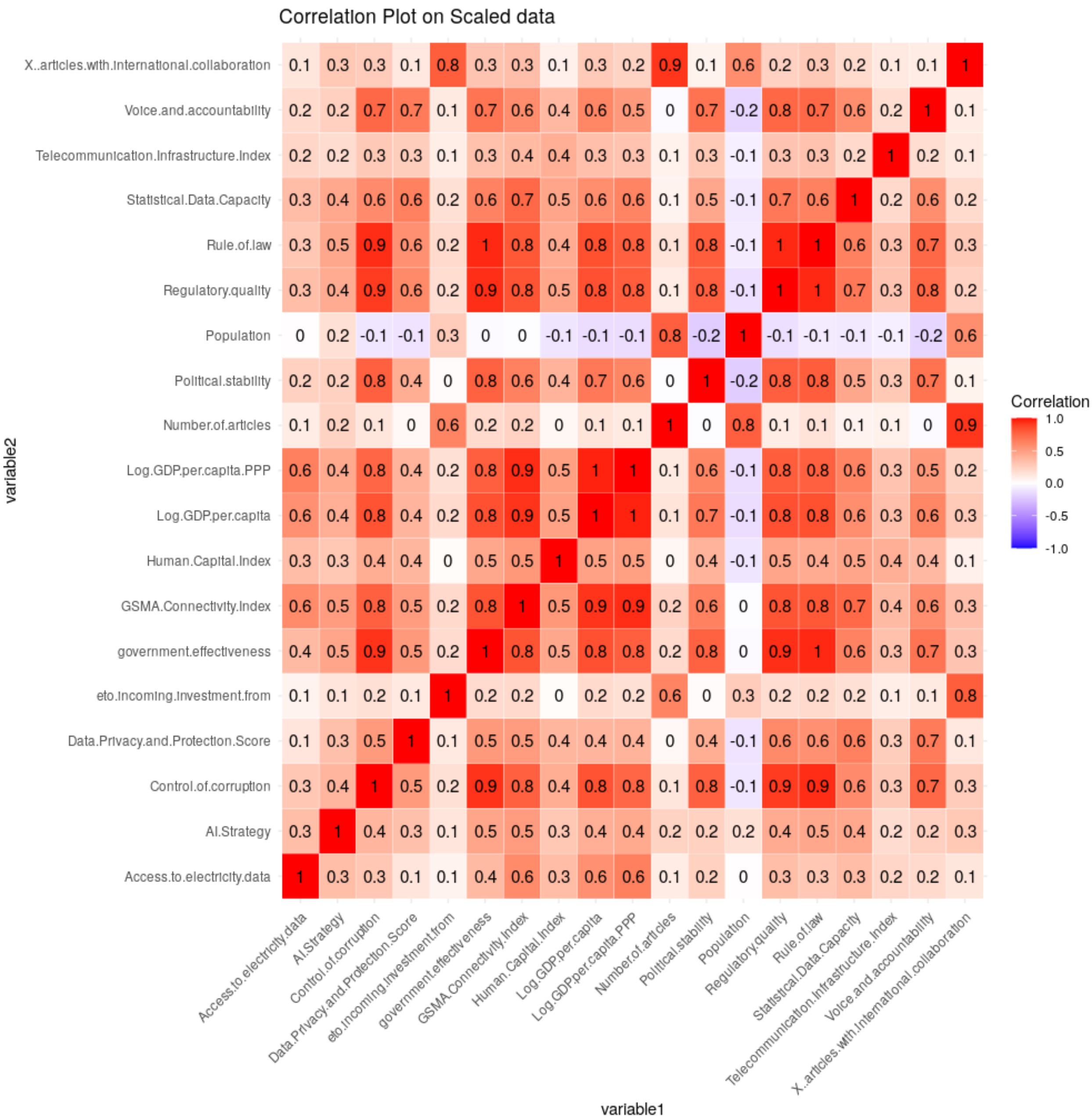
The principal indicators utilized to develop the AI Investment Potential Index (AIIPI) are as follows: **Access to Electricity**, the **GSMA Connectivity Index**, and the **Telecommunication Infrastructure Index**, which represent the foundational infrastructure necessary for the deployment of AI technologies. Economic measures such as **Log GDP per Capita PPP** and **Population** assess a country's market potential and financial capacity to support AI growth. Governance-related indicators, including **Government Effectiveness**, **Political Stability**, and **Voice and Accountability**, evaluate the quality of public services, political climate, and regulatory framework, all of which are crucial for long-term AI investments. The **Human Capital Index** measures the availability of skilled talent, while innovation capacity is reflected in the **Number of Research Articles** and **Statistical Data Capacity**, representing a country's research ecosystem and data management capabilities. Additionally, the presence of a national **AI Strategy** and the **Data Privacy and Protection Score** highlight a government's commitment to fostering AI development and ensuring data security.

These indicators, collectively, provide a comprehensive framework for evaluating a country's AI investment potential by addressing critical factors related to infrastructure, governance, economic capacity, human capital, and innovation.

3.1. Scaling and Normalization

All indicators were normalized using min-max scaling, transforming each metric to a range of $[0, 100]$ to allow comparability across indicators. In instances of high correlation between indicators, such as GDP per Capita and GDP per Capita PPP, only the more informative measure (GDP per Capita PPP) was retained.

Figure 1. Correlation Plot on Scaled data



The formula used for scaling is:

$$Scaled\ Value = \frac{(X - X_{min})}{(X_{max} - X_{min})} * 100$$

Where X represents the original value, X_{min} is the minimum observed value, and X_{max} is the maximum observed value for the variable.

Variables with missing values (NA) were rescaled by excluding these values when determining the minimum and maximum. If all values were missing, no scaling was applied, and the original values were retained. When all non-missing values were identical (i.e., X_{min}= X_{max}), all observations were assigned a value of 100 to avoid division by zero. Table 3 (See Annex 2) shows the minimum and maximum value of the unscaled variables, Table 1 displays the descriptive statistics of the scaled variables and Figure 1 represents the correlation plot on scaled data.

Table 1. Descriptive Statistics of Scaled Variables

Variable	Mean	Median	SD	IQR	Skewness	Kurtosis	ShapiroP[3]	Missing
Incoming.Investment	1.75	0.095	9.29	0.617	9.74	101	0	0
AI.Strategy	60.6	100	46.4	100	-0.433	1.31	0	6
Access.to.electricity.data	93.3	100	19.4	0.331	-3.23	12.5	0	8
GSMA.Connectivity.Index	62.6	64.4	24.3	37.8	-0.51	2.49	0	10
Data.Privacy.and.Protection.Score	72.4	100	32.5	50	-0.759	2.52	0	0
Log.GDP.per.capita.PPP	60.1	62.7	20.3	27.6	-0.51	2.8	0	4
Government.Effectiveness	52.3	49.2	20.9	31.8	0.14	2.29	0.009	8
Human.Capital.Index	71.2	74.1	19.1	24.8	-1.09	4.08	0	8
Telecommunication. Infrastructure.Index	62	64.9	24.1	34.7	-0.548	2.46	0	8
Political.Stability	63.2	65.5	20.6	30.4	-0.502	2.82	0	8
Population	4.25	0.791	13.3	2.87	6.42	45.7	0	2
Voice.and.Accountability	54.3	56.4	27	44.9	-0.274	1.97	0	8
Number.of.Articles	3.66	0.624	11.5	2.28	6.5	49.8	0	4
Statistical.Data.Capacity	69.9	74.3	20.9	35.2	-0.612	2.59	0	9

[3] Note: If the Shapiro-Wilk p-value (ShapiroP) is greater than 0.05, it suggests that the variable is likely normally distributed. Shapiro-Wilk Test is more effective for smaller datasets (typically < 5000 observations).

3.2. Model Development and Weighting Strategy

The "incoming AI investment counts" indicator was selected as the target variable to assess the attractiveness of countries for AI investments. This variable was linked to a carefully selected subset of 13 key indicators, including AI strategy, political stability, GSMA connectivity, and statistical data capacity. Data from 2020 and 2022 were analyzed to identify key factors that most strongly predict AI investment potential. This analysis provided a solid foundation for model evaluation and informed the development of the AI Investment Potential Index (AIIPI), with the 2022 data playing a central role in constructing the final index.

To construct the AIIPI, we considered three modeling approaches along with an entropy-based weighting method (Roszkowska *et al.*, 2024) to determine the optimal weightings for each indicator. **Linear models** were initially applied to establish a baseline understanding of the relationships between the indicators and the target variable, highlighting which predictors had significant associations. These models provided essential insights into linear interactions between variables. Building on this, **Elastic Net Regression** was employed to address multicollinearity among the indicators. By combining L1 (lasso) and L2 (ridge) regularization techniques, Elastic Net balanced feature selection with model stability. A grid search was utilized to optimize key hyperparameters—penalty (lambda) and mixture (alpha)—while five-fold cross-validation ensured robust model performance and minimized overfitting.

Additionally, **Random Forests**, a non-linear ensemble learning technique, was implemented to capture complex interactions between the indicators. This method was particularly useful for identifying the most important features across a wide range of socio-economic variables. The Random Forest model was tuned to find the optimal number of predictors at each split and the minimum number of observations in terminal nodes. Cross-validation was employed, and the model selection was based on minimizing Root Mean Square Error (RMSE) to ensure accuracy in predicting AI investment potential.

The model development process followed a structured pipeline. The dataset was split into training (80%) and testing (20%) subsets to ensure generalizability. During data preprocessing, missing values were imputed using median replacement for numeric predictors, preserving dataset integrity and avoiding potential biases. Hyperparameter tuning for both the Elastic Net and Random Forest models was conducted via grid search techniques—**grid_max_entropy** for Elastic Net and **grid_regular** for Random Forest—to systematically explore the parameter space and assess the impact of different configurations on model performance. Five-fold cross-validation was applied across all models to enhance parameter estimation and reduce the risk of overfitting, providing a robust and reliable model development process.

In addition to the three modeling approaches, an **entropy-based weighting method** was considered to evaluate indicator importance based on the variability within the dataset. This method was particularly effective for handling skewed distributions, as it assigns greater weight to indicators with higher variability. By incorporating this method, we gained further insights into the uniqueness and spread of the data, refining the overall weighting strategy used in the development of the AIIPI.

3.3. Model Evaluation

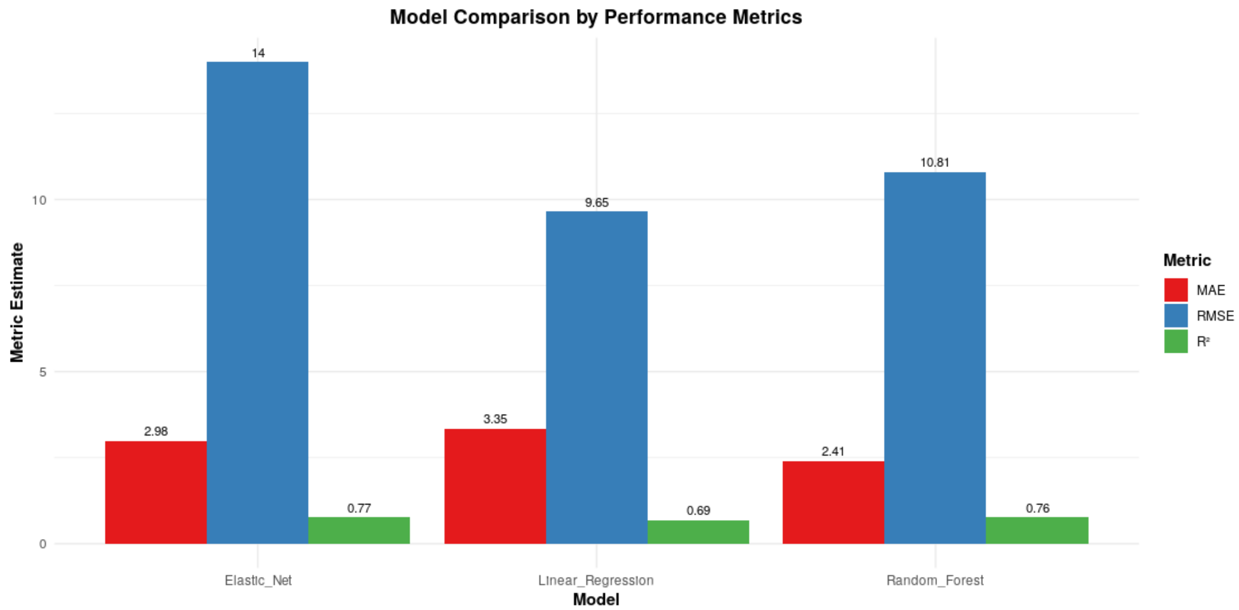
The model performance on unseen data was assessed using Root Mean Square Error (RMSE), R-squared (R^2), and Mean Absolute Error (MAE) to compare the Elastic Net, Linear Regression, and Random Forest models. Figure 2 summarizes the performance metrics obtained for each model.

The Elastic Net model showed a balanced performance with an RMSE of 14.0 and an R^2 of 0.773, explaining 77.3% of the variance in AI investment potential. Its MAE of 2.98 indicated moderate average prediction error. The model's combination of L1 and L2 regularization effectively addressed multi-collinearity, making it particularly useful for socio-economic datasets with correlated variables. Additionally, Elastic Net's feature selection capability helped manage model complexity.

In contrast, the Linear Regression model had a lower R^2 of 0.690, indicating a weaker fit, and a higher MAE of 3.35, suggesting greater variability in individual predictions. Despite having a lower RMSE of 9.65, Linear Regression's inability to capture non-linear relationships limited its performance in this context. Its main advantage was its simplicity and ease of interpretation.

The Random Forest model demonstrated strong performance by minimizing extreme errors, achieving the lowest MAE of 2.41 and an R^2 of 0.762. With an RMSE of 10.8, it performed between Elastic Net and Linear Regression. Random Forest's non-linear nature allowed it to capture complex relationships among the variables, making it particularly effective in scenarios where reducing large errors was critical. Additionally, its ability to provide feature importance offered valuable insights into the key factors influencing AI investment potential.

Figure 2. Model Comparison by Performance Metrics



3.4. Weighting Insights from Different Models

Weights were derived based on the variable importance from each model and subsequently normalized so that their sum equals 1, allowing them to be interpreted as proportions or percentages, thereby enabling direct comparison across variables.

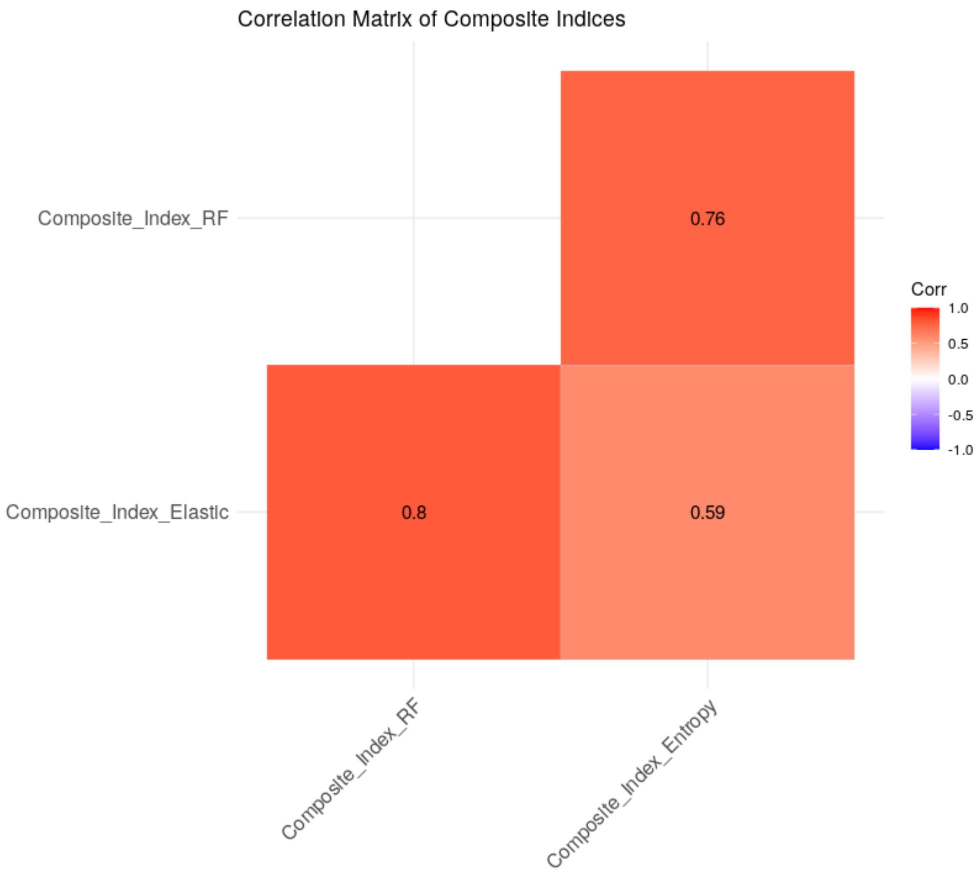
In the **Elastic Net model**, the highest weights were assigned to the *Number of Articles Published* (45.0%) and *Population* (23.5%), underscoring the pivotal role of a robust research ecosystem and market size in attracting AI investments. Other significant contributors included the *GSMA Connectivity Index* (6.4%), *Statistical Data Capacity* (4.8%), and *Political Stability* (4.0%), indicating that innovation capacity, population size, and digital infrastructure are key factors for AI adoption.

The **Random Forest model** produced a different weighting distribution, with *Population* (20.3%), *Number of Articles Published* (13.0%), and *GSMA Connectivity Index* (12.7%) as the top contributors. Additionally, the model placed considerable importance on *Government Effectiveness* (10.9%) and *Political Stability* (10.4%), highlighting the crucial role of governance and infrastructure in creating an attractive environment for AI investments. The spread of weights among these indicators emphasized the model's focus on governance quality and digital readiness as foundational elements for successful AI implementation.

The **Entropy-Based Weighting** method emphasized the significance of the *Number of Articles Published* (36.3%) and *Population* (34.5%), with *AI Strategy* (10.4%) also emerging as a notable contributor. This approach reinforced the importance of a proactive national AI strategy, a strong research base, and market size in drawing AI investments. The entropy-based method's reliance on variability allowed it to capture unique aspects of each indicator, particularly highlighting those with greater diversity across countries, making it a valuable complement to the other models by emphasizing different dimensions of importance.

Furthermore, the correlation analysis results, reported in Figure 3, revealed strong alignment of composite index based on the weights from Elastic Net model and the index based on the weights from the Random Forest models, with both identifying key drivers of AI investment potential, such as the number of AI-related articles and population size. Despite methodological differences, these models consistently highlighted similar factors, reinforcing the robustness of the AI Investment Potential Index (AIIPI).

Figure 3. Correlation Matrix of Composite Indices



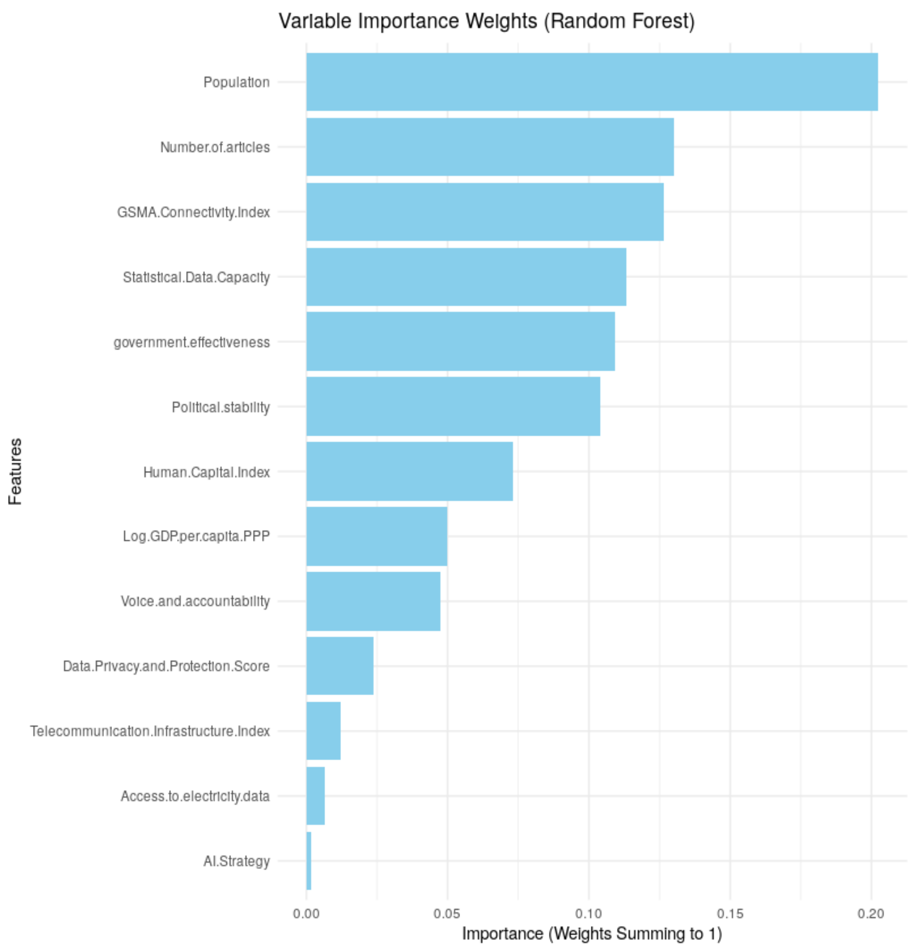
In contrast, the entropy-based weighting method provided a distinct perspective, placing greater emphasis on population size and research output, while also giving significant weight to AI strategies and other country-specific attributes. This approach captured additional variability, offering a complementary view of AI investment potential, enriching the overall analysis with insights not emphasized by the other models.

This comparative analysis of the weighting approaches illustrates how each method brings a unique perspective, allowing for a nuanced understanding of the factors driving AI investment decisions.

3.5. Variable Importance from Best Performing Model - Random Forest

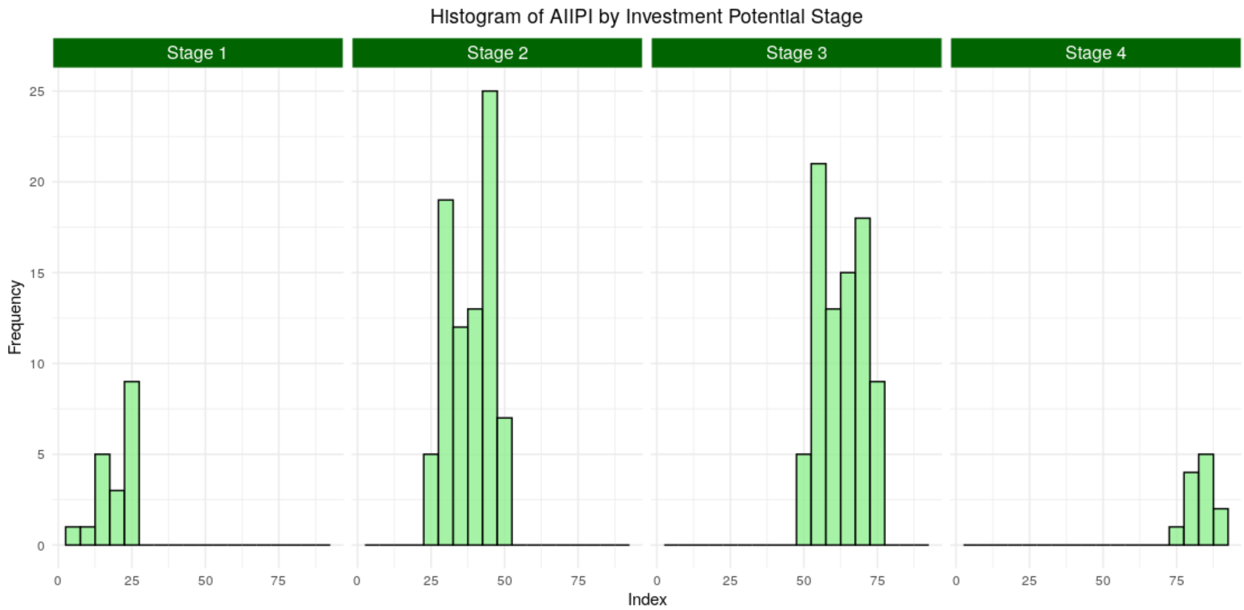
In the random forest model, which was the **best performing model** on unseen data, the variable importance analysis revealed several key factors influencing AI investment attractiveness (See Figure 4; Annex 2, Table 4). *Population*, accounting for 20.3% of the variable importance, emerged as a major driver, suggesting that larger populations offer greater market expansion opportunities and workforce availability, thereby aligning with the economies of scale necessary for AI technology adoption. The *number of research articles*, contributing 13.0%, was a strong indicator of a country's innovation capacity, correlating directly with increased AI investments. This highlights the importance of advanced knowledge ecosystems, as countries with significant research outputs are better positioned for AI development and implementation. The *GSMA Mobile Connectivity Index*, at 12.7%, emphasized the critical role of digital infrastructure in AI deployment, particularly in developing economies where mobile connectivity is essential for both data collection and operational execution of AI technologies.

Figure 4. Variable Importance Weights (Random Forest)



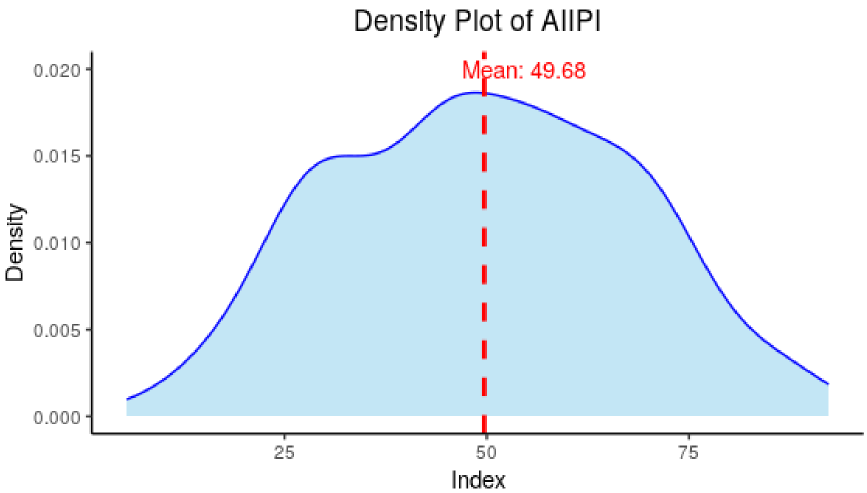
Other influential variables included *Statistical Data Capacity* (11.3%) and *Government Effectiveness* (10.9%), both of which underscored the importance of governance and data readiness. Countries with the ability to efficiently collect and process data, alongside robust governmental structures, were more likely to attract AI investments. Finally, *Political Stability*, comprising 10.4% of variable importance, was identified as a pivotal factor. Stable political environments offer predictability for investors, making such countries more appealing for long-term AI projects due to reduced risks and uncertainties in governance. These findings underscore the multifaceted nature of AI investment decisions, where population size, innovation capacity, digital infrastructure, data governance, and political stability collectively shape the landscape.

Figure 5. Histogram of AIIPI by Investment Potential Stage



The analysis of AIIPI scores reveals distinct trends across investment potential stages (See Figure 5). The stages are defined as follows: Stage 1 (AIIPI < 26), Stage 2 (AIIPI between 26 and 50), Stage 3 (AIIPI between 51 and 75), and Stage 4 (AIIPI >= 76). Stages 2 and 3 show a clustering of scores around the median, indicating stability, whereas Stages 1 and 4 exhibit lower frequencies and narrower distributions. The density plot (See Figure 6), centered around a mean of 49.68, suggests a balanced dispersion of investment potentials, with most opportunities falling within a mid-level potential range, offering a moderate risk-reward profile.

Figure 6. Density Plot of AIIPI



4. Analysis and Findings

This section delves into a comprehensive analysis of the AI Investment Potential Index (AIIPI[4]), exploring its performance at both continental and regional levels. The AIIPI provides new insights into the readiness and attractiveness of countries for AI investments, distinctively positioning itself from existing indices such as the Oxford Insights Government AI Readiness Index and the IMF AI Preparedness Index (Annex 4, Table 5). By comparing these indices, we highlight the unique factors captured by AIIPI that enhance its predictive value. Furthermore, this analysis identifies key patterns between AIIPI and other economic indicators, such as income levels, offering a deeper understanding of how AI investment potential aligns with broader development trends across regions.

4.1 Continental and Regional Insights

Map 1 provides an overview of the AI investment potential in the world while Figures 7 and 8 summarize the investment potential stages at regional and continent levels, revealing a significant disparity in investment attractiveness (See Annex 3 on Geographical Maps of AIIPI). Europe and North America lead with the highest scores (66.41 and 70.5, respectively), indicating a strong capacity for attracting investment. These regions show well-established infrastructure, economic stability, and favorable regulatory environments, placing them in Stage 3 of investment potential.

[4] The AIIPI data is publicly accessible: https://www.data.gouv.fr/fr/datasets/index-du-potentiel-dinvestissement-dans-lia-2024/

Map 1. AI Investment Potential Index in the World

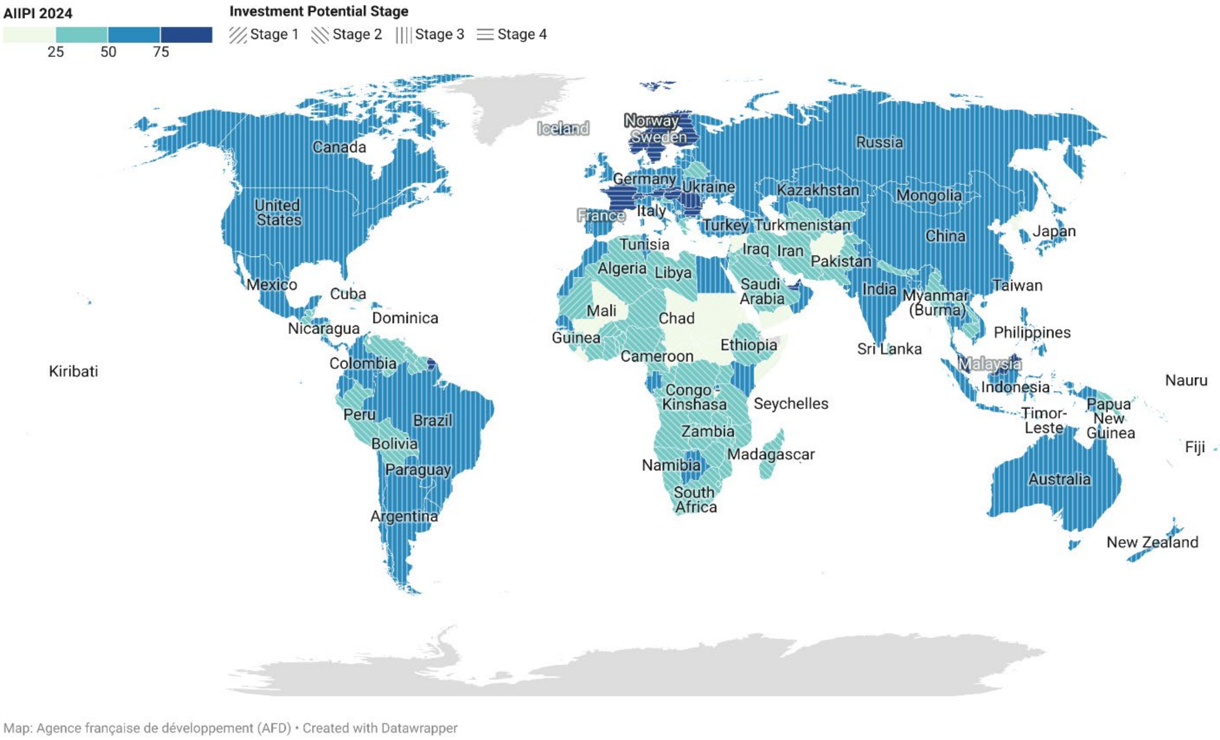
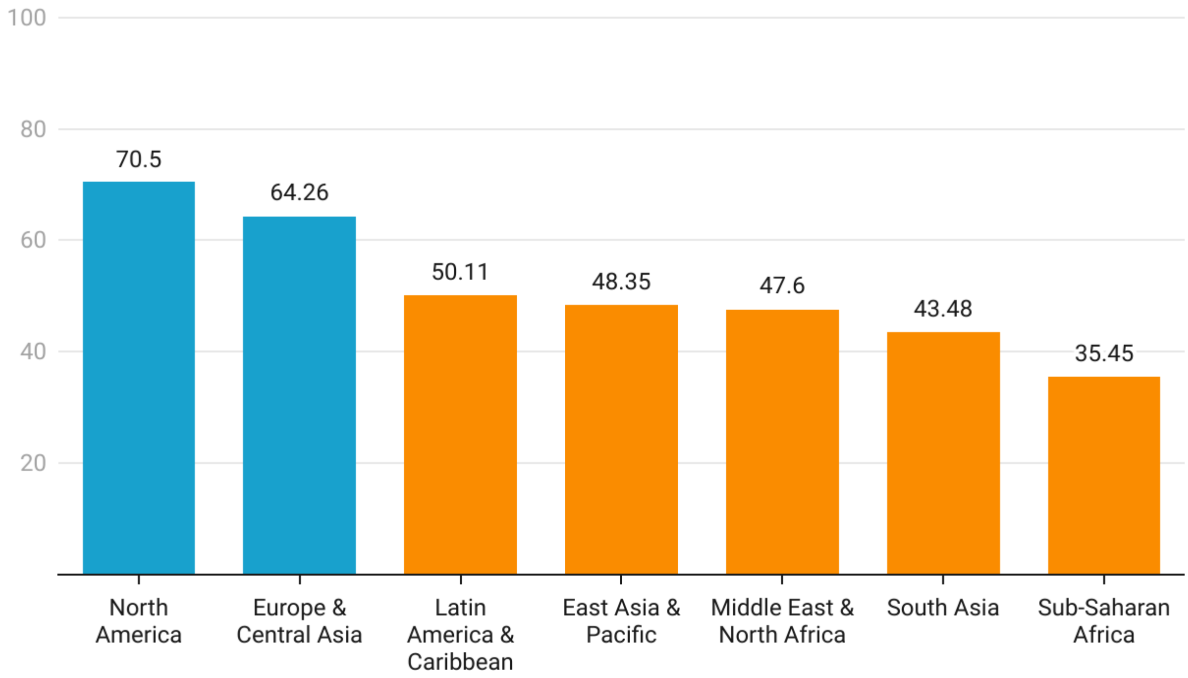


Figure 7. Investment Potential Stages by Region

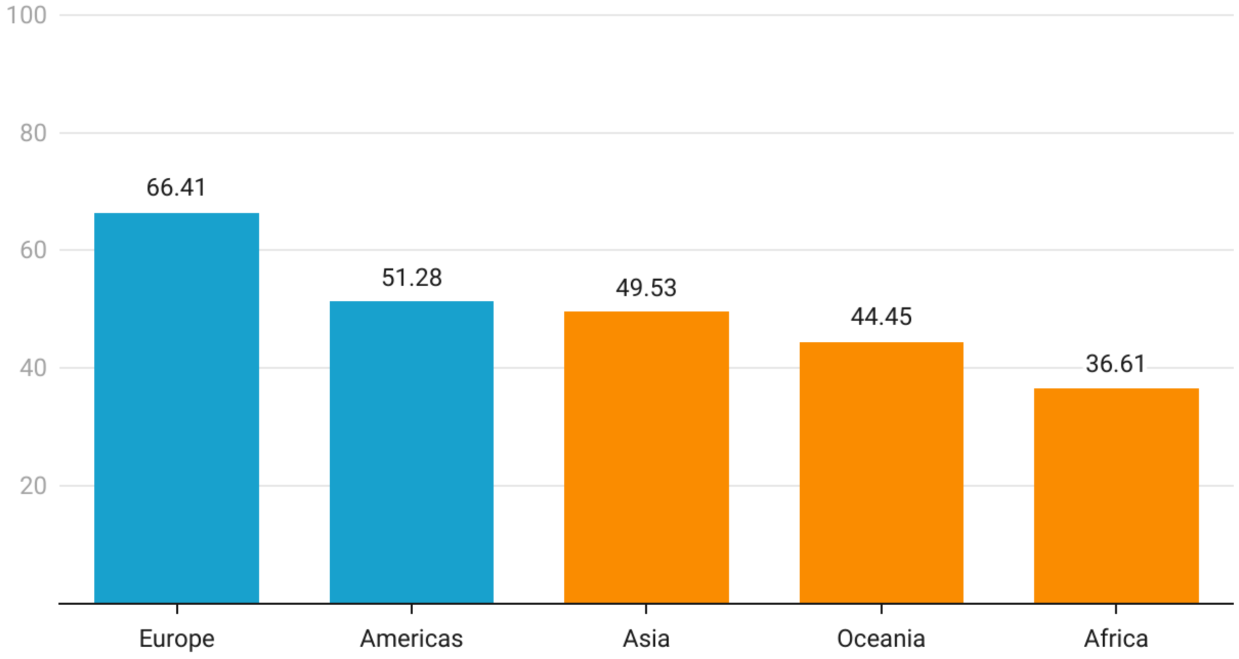


The colors correspond to the investment potential stage, where Stage 2 is Orange and Stage 3 in Blue.

Created with Datawrapper

In contrast, regions like Sub-Saharan Africa (35.45) and Africa as a whole (36.61) are in Stage 2, reflecting more challenging investment climates. These areas might face barriers such as political instability, limited infrastructure, or underdeveloped financial systems, which make them less attractive to investors compared to their counterparts. The consistent gap between continents and sub-regions, especially between Europe and Sub-Saharan Africa, underscores the need for targeted policy interventions and developmental aid to bridge the gap in investment attractiveness and attract greater economic engagement globally.

Figure 8. Investment Potential Stages by Continent



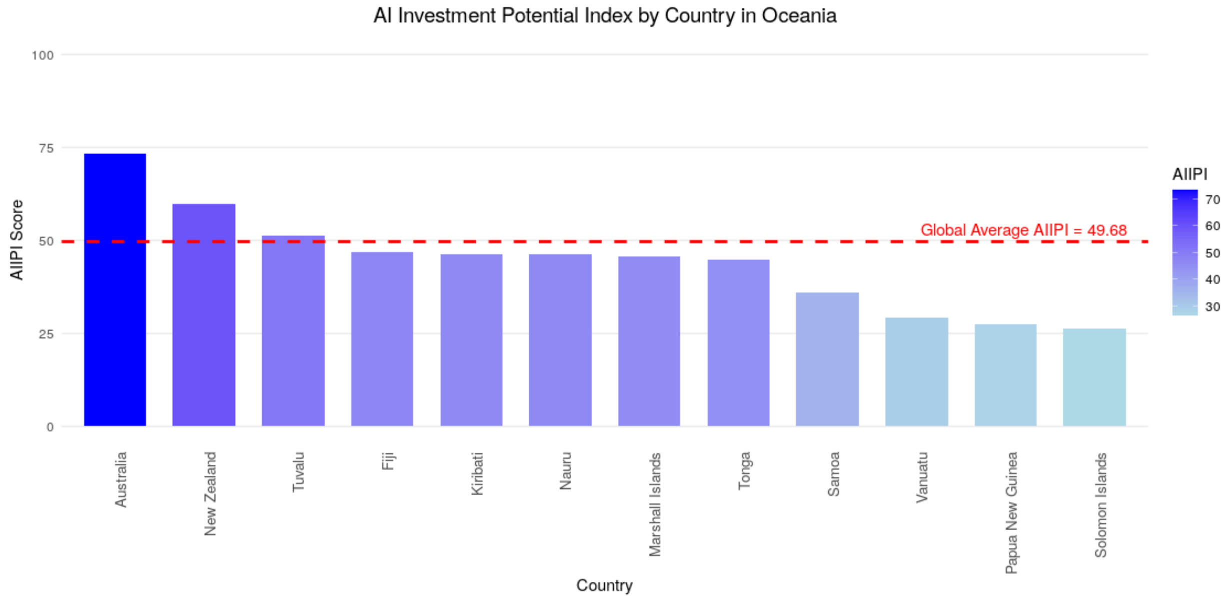
The colors correspond to the investment potential stage, where Stage 2 is Orange and Stage 3 in Blue.
Created with Datawrapper

These findings highlight the critical role of regional differences in shaping investment decisions, with distinct clusters of opportunities and challenges that demand tailored strategic approaches for each area.

The AIIPI evaluates AI investment attractiveness across continents, revealing regional disparities and underscoring the necessity for targeted investment strategies. Figures 9, 10, 11, 12 and 13 show the AIIPI scores obtained by countries, respectively for Oceania, Africa, Americas, Asia and Europe.

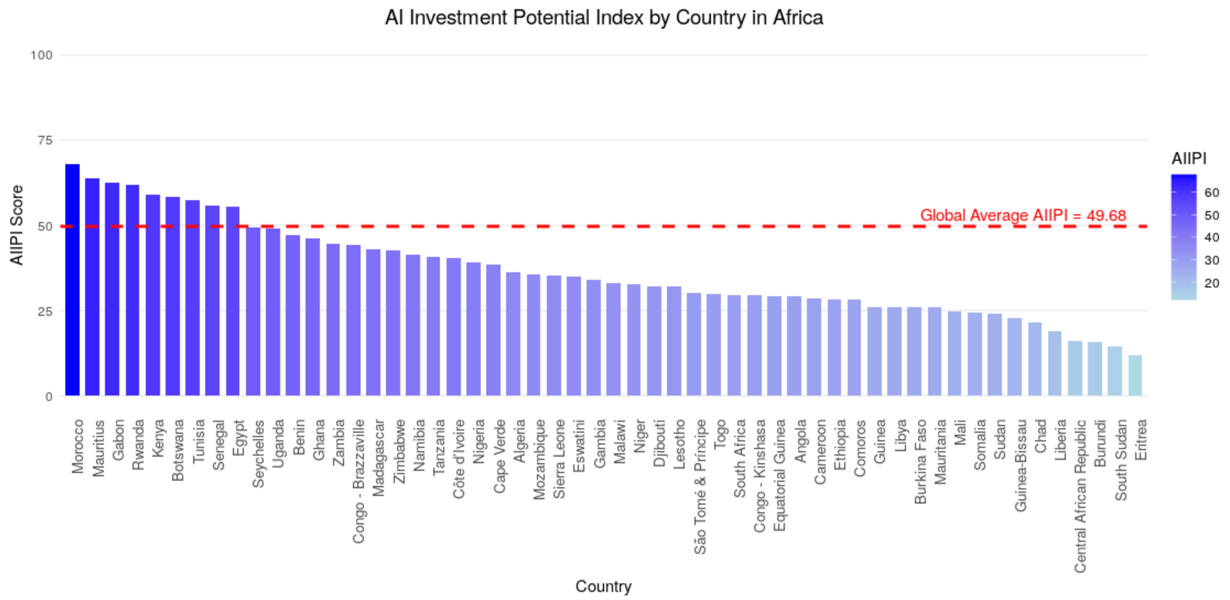
- **Oceania**: Australia and New Zealand lead in AI investment potential, whereas countries like Vanuatu and Papua New Guinea lag due to deficiencies in digital infrastructure. Investments in AI literacy and telecommunications are crucial for smaller island nations. Enhancing internet accessibility and government-led initiatives could play a key role in bridging these gaps.

Figure 9. AI Investment Potential Index by Country in Oceania



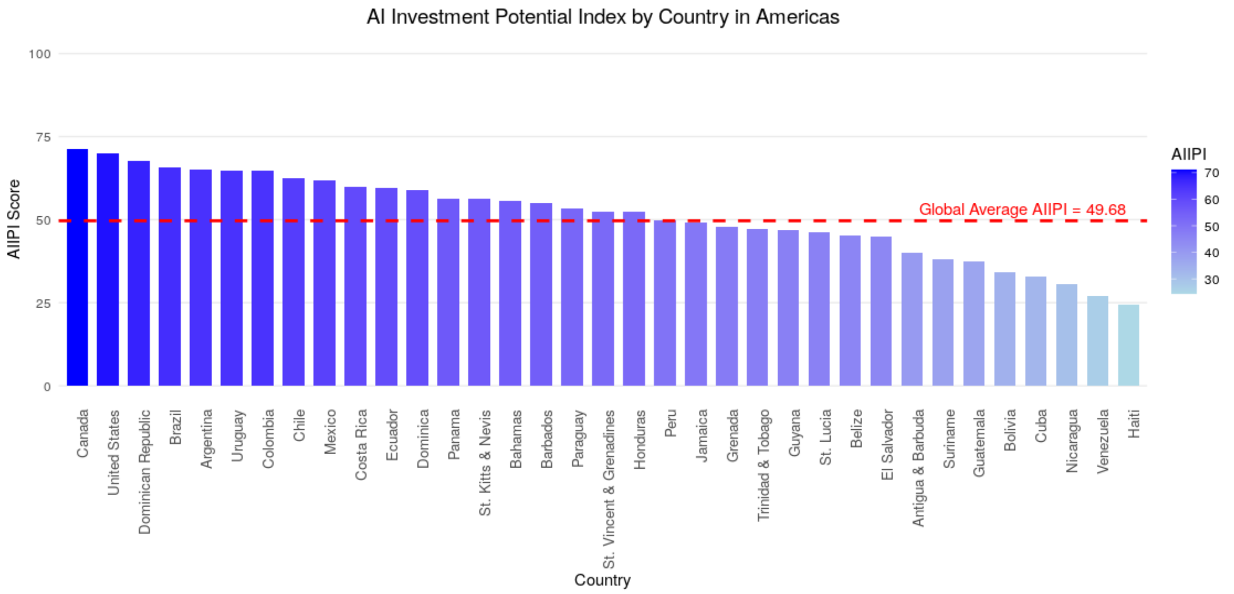
- **Africa**: Morocco, Mauritius, and Gabon are leaders, while countries like Eritrea and South Sudan exhibit significant gaps in infrastructure and digital readiness. Establishing local AI hubs, fostering international collaborations, and enhancing workforce skills can substantially improve AI attractiveness. Public-private partnerships are also vital in addressing infra-structural shortcomings.

Figure 10. AI Investment Potential Index by Country in Africa



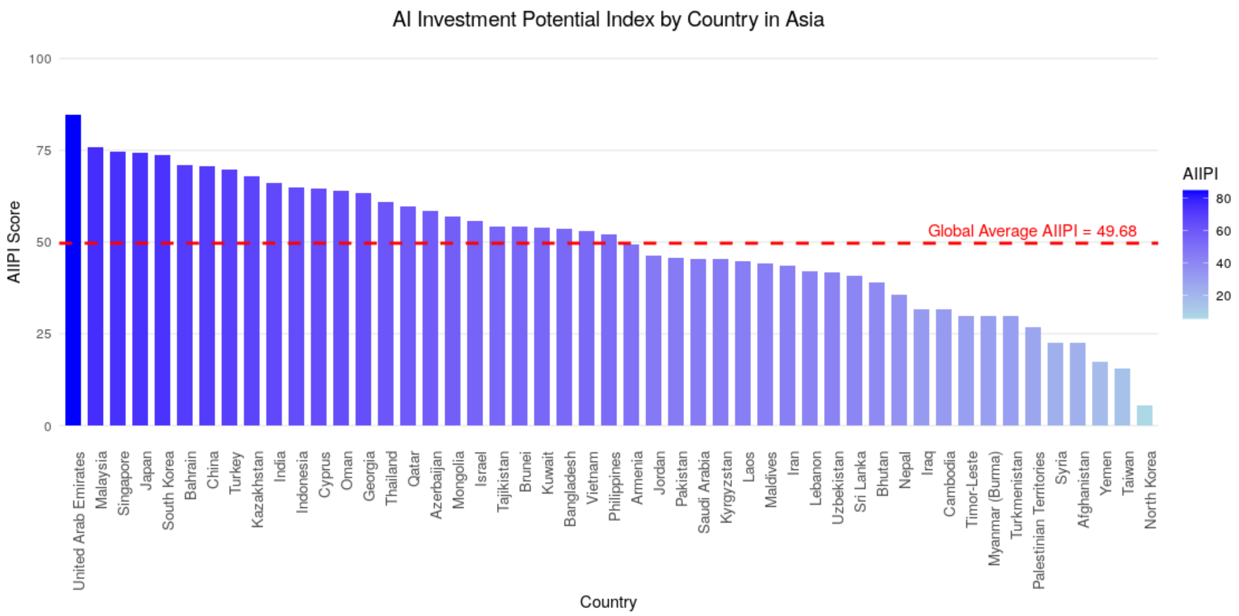
- **Americas**: The U.S. and Canada rank highest, followed by Brazil and Argentina. However, countries like Venezuela face considerable challenges, including economic instability and weak governance, which hinder their AI potential. Policy interventions that focus on stabilizing governance and building foundational digital infrastructure can significantly bolster AI readiness in these nations.

Figure 11. AI Investment Potential Index by Country in Americas



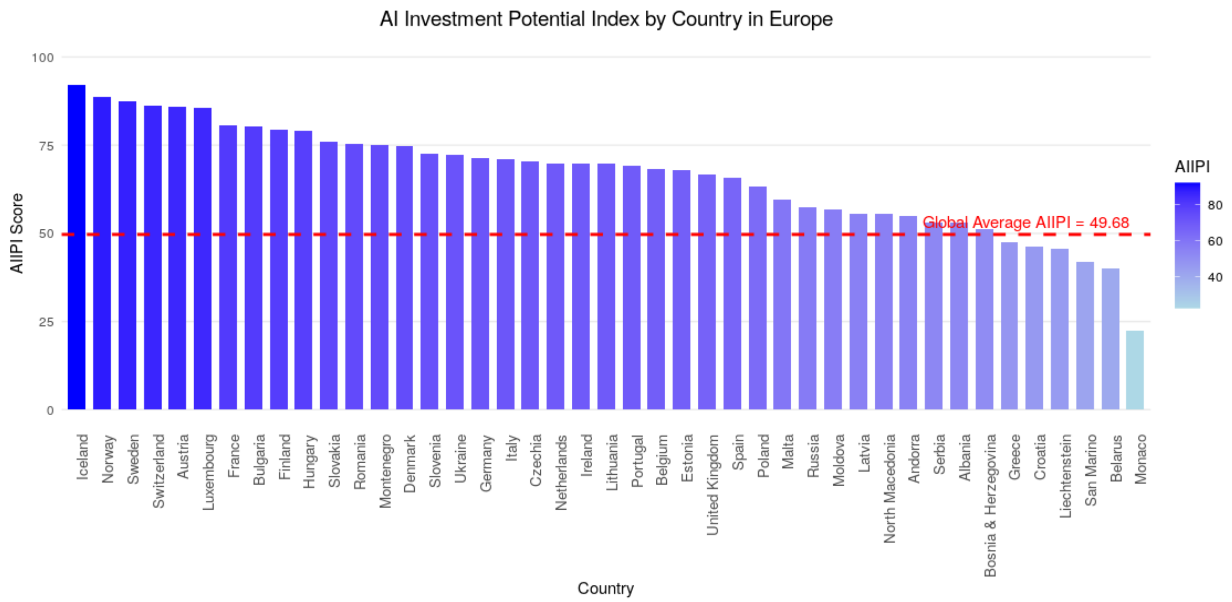
- **Asia**: The UAE, Singapore, and Japan top the AI readiness rankings, benefiting from robust government initiatives, advanced technological infrastructure, and proactive AI policies. In contrast, Afghanistan and Yemen require foundational infrastructure investments. Regional cooperation to share technological expertise and resources could help elevate AI investment attractiveness across less developed parts of Asia.

Figure 12. AI Investment Potential Index by Country in Asia



- **Europe**: Northern and Western Europe outperform Eastern Europe, reflecting higher levels of digital readiness, government support, and research intensity. Targeted investments in digital infrastructure, cohesive AI policies, and cross-border collaborations could help Eastern European nations catch up with their Western counterparts.

Figure 13. AI Investment Potential Index by Country in Europe



4.2. Trends and patterns observed

AIIPI vs. Oxford Insights Government AI Readiness Index and IMF AI Preparedness Index

To contextualize the AIIPI's distinctiveness, we compared it with two established indices: the IMF AI Preparedness Index and the Oxford Insights Governance AI Readiness Index (Annex 4, Table 5) details the differences in definitions and methodologies. Figure 14 presents the correlation coefficients among these indices, highlighting both overlaps and unique aspects of the AIIPI.

A high correlation of **0.9412** is observed between the IMF AI Preparedness Index and the Oxford Insights Governance AI Readiness Index, indicating significant overlap in their focus on governance quality, regulatory frameworks, and institutional strength.

The AIIPI shows a strong correlation of **0.8295** with the IMF index, suggesting that countries scoring high on the IMF index also perform well on the AIIPI. This overlap indicates that governance quality, infrastructure, and economic conditions are contributing factors for both indices.

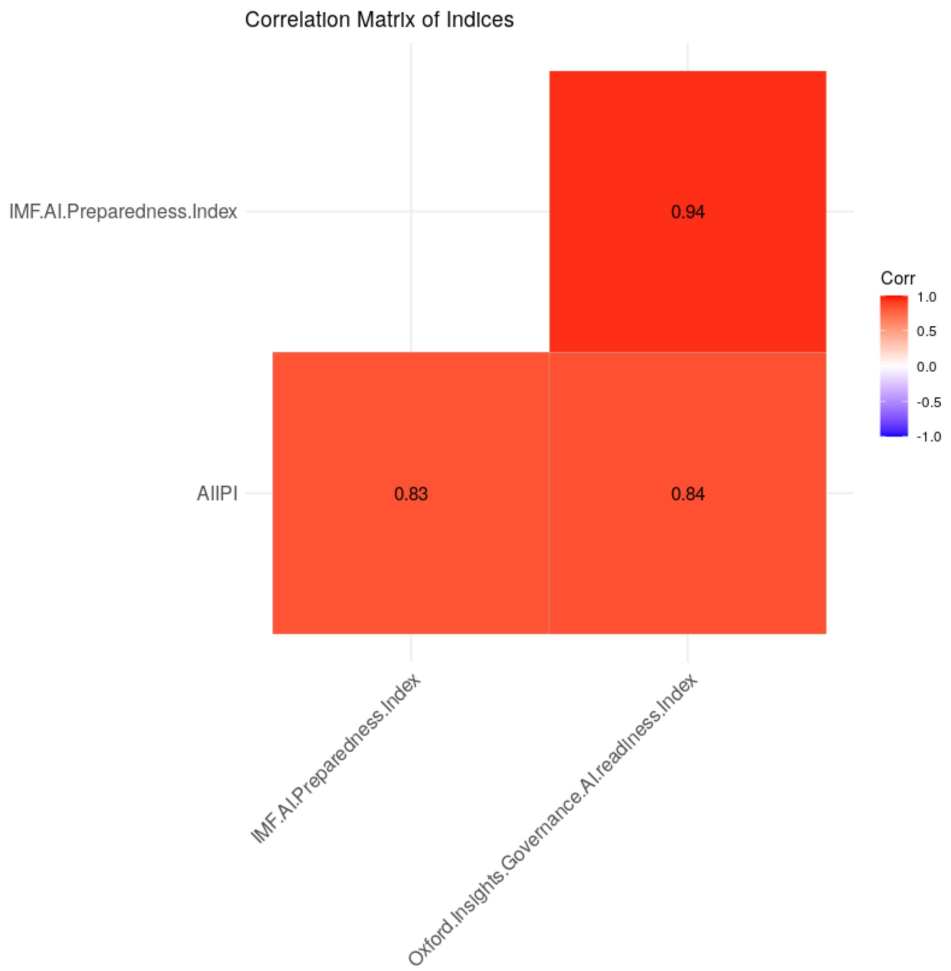
Similarly, the correlation between the AIIPI and the Oxford Insights index is **0.8359**. This strong relationship suggests that effective governance, as assessed by the Oxford Insights index, closely aligns with the conditions that promote AI investment potential.

Distinctiveness of the AIIPI

While the AIIPI aligns well with these indices, it uniquely focuses on the specific dynamics that enhance a country's attractiveness for AI investments. By incorporating additional investment-oriented, economic, and market-specific indicators, the AIIPI provides a tailored analysis of the conditions that investors prioritize.

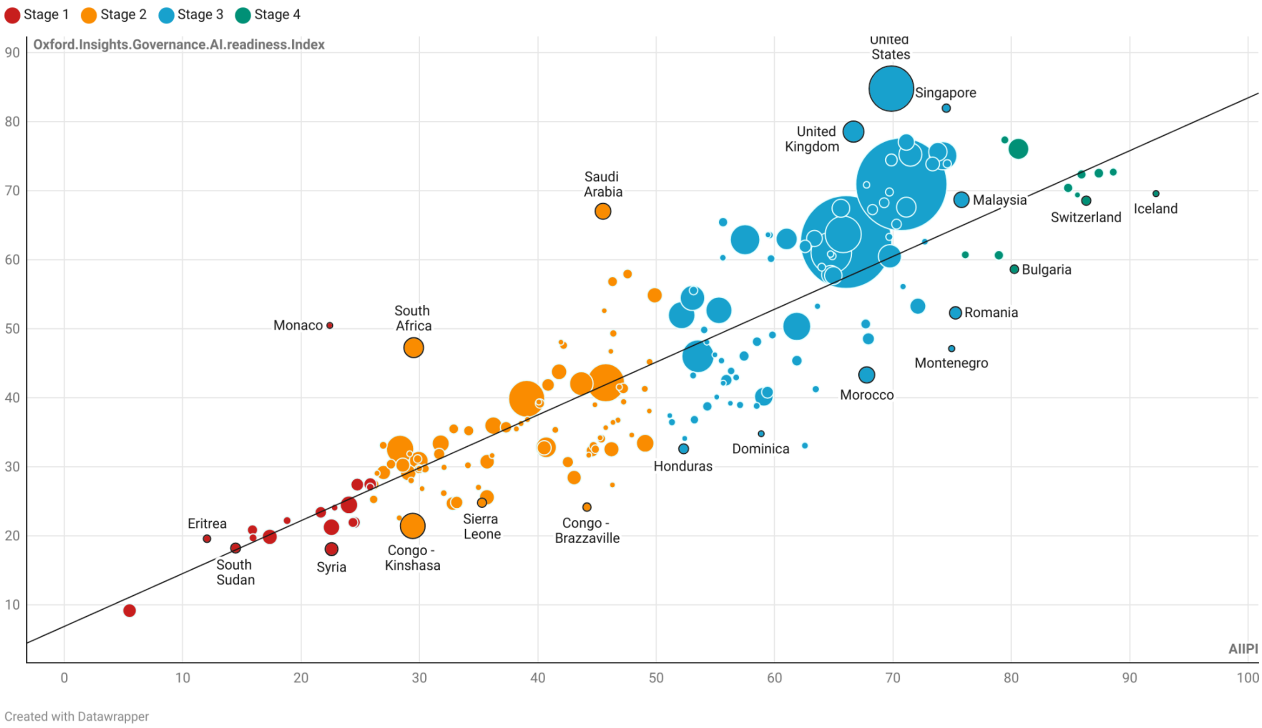
The slightly lower correlation coefficients – **0.8295** with the IMF and **0.8359** with Oxford Insights – underscore the AIIPI's unique perspective. This enhanced focus on economic performance, market potential, and direct policy incentives makes the AIIPI particularly valuable for stakeholders seeking a deeper understanding of the AI investment landscape. It serves as a complementary tool that enriches traditional readiness measures, offering comprehensive insights into AI investment potential across different regions.

Figure 14. Correlation of AI Investment Potential Index (AIIPI) with Existing Indices



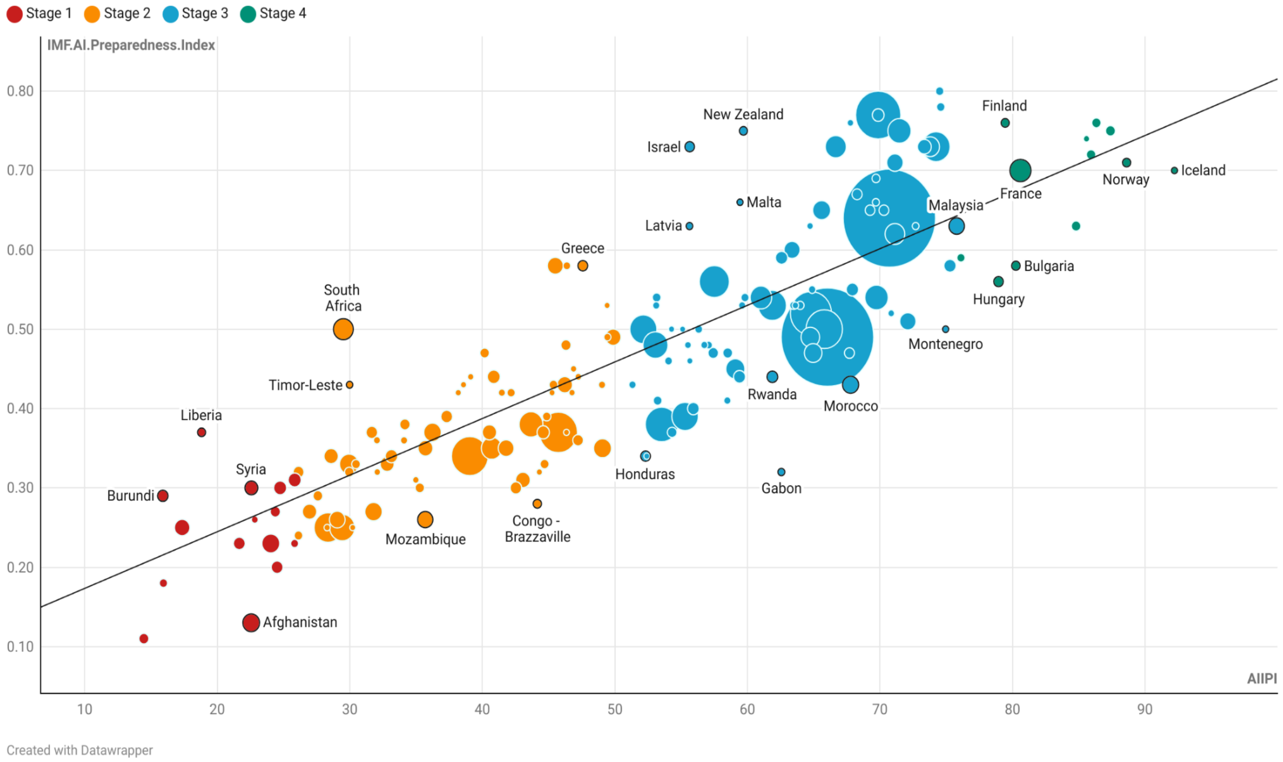
It is worth noting that countries positioned in Stages 3 and 4 (marked in blue and green, respectively) generally exhibit higher governance and AI readiness capacities, as highlighted by comparisons with both the Oxford Insights Government AI Readiness Index and the IMF AI Preparedness Index (See Figures 15 and 16). These indexes provide an important validation for the trends observed in AIIPI scores.

Figure 15. Correlation between AIIPI and Oxford Insights Index and Countries Stages



The alignment of higher AIIPI scores with these established indexes demonstrates a strong correlation between well-developed governance frameworks and an environment conducive to AI adoption and scalability. Stage 2 countries (in orange) appear to be in a transitional phase, exhibiting moderate readiness but lacking the advanced governance attributes that characterize Stage 3 and 4 nations, as captured by the Oxford and IMF indexes. In contrast, Stage 1 countries (in red) show lower governance capacity and AI readiness, reflecting significant barriers—consistent with the scores reported in the Oxford and IMF indicators—to adopting advanced AI infrastructure.

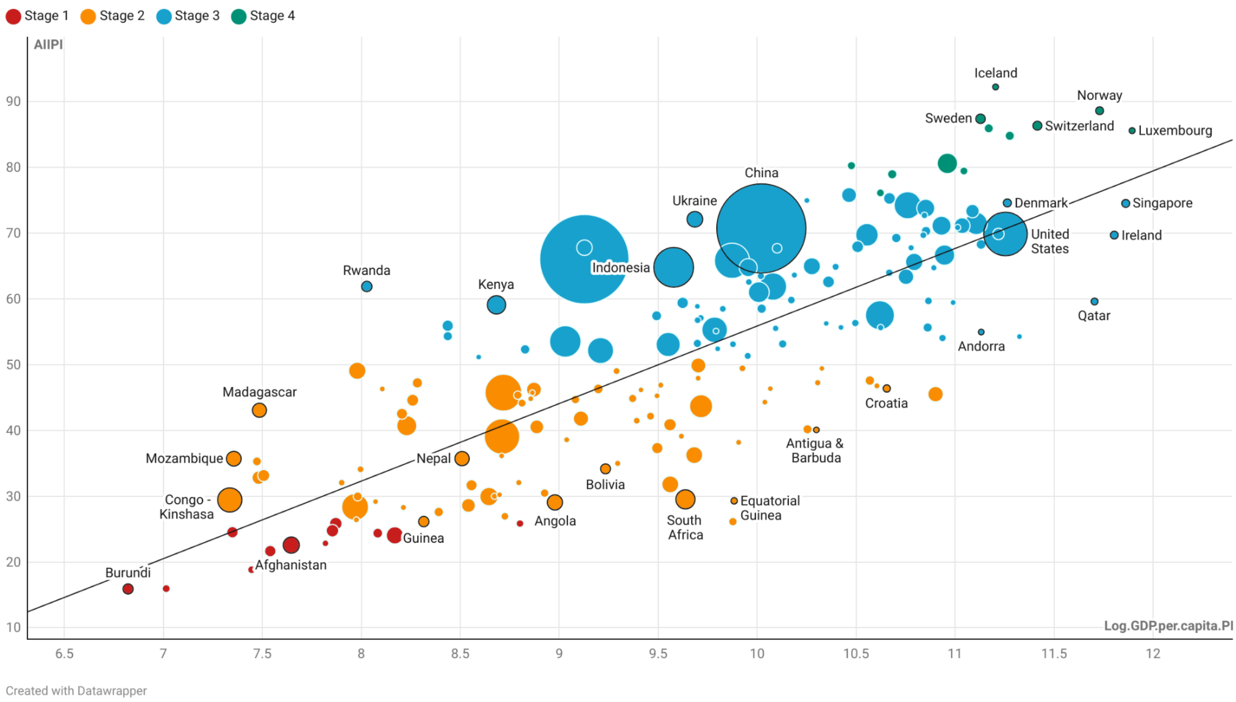
Figure 16. Correlation between AIIPI and the IMF Preparedness Index and Countries Stages



Correlation between AIIPI and other indicators

The positive correlation between AIIPI and GDP per capita indicates that economic wealth is a significant determinant of AI investment potential (See Figure 17). Stage 4 countries, characterized by high AIIPI scores, are concentrated among high GDP per capita nations, implying that wealthier countries are better equipped to foster a conducive environment for AI development. In contrast, Stage 1 and 2 countries with lower AIIPI are mostly in the lower GDP range, highlighting how economic limitations can restrict both investments and the infrastructure necessary for AI growth.

Figure 17. Correlation between AIIPI and GDP per Capita and Countries Stages



Notable regional outliers, such as Singapore and Iceland, consistently appear at the upper end of readiness and connectivity indicators, demonstrating the distinct policy frameworks and infrastructure these countries have implemented to maintain AI competitiveness. Conversely, nations such as Afghanistan, South Sudan, and Burundi are repeatedly positioned at the lower end of the spectrum across different indicators, revealing systemic challenges that hinder their AI adoption capabilities.

Furthermore, our analysis also reveals that effective governance and robust connectivity infrastructure are essential but interdependent drivers of AI investment potential. The clustering of nations in Stages 3 and 4, both in terms of government effectiveness and connectivity scores, indicates that the most significant strides in AI development are made when both elements are present and mutually reinforcing. For countries seeking to enhance their AI investment potential, this calls for an integrated approach: strengthening institutional quality, expanding communication networks, and improving statistical data capabilities. By focusing on these interlinked factors, governments can foster an environment that not only attracts AI investment but also supports sustainable development of AI ecosystems. Countries in lower stages, especially those with weak governance and limited connectivity, must prioritize these foundational areas, as addressing both concurrently can significantly amplify their AI readiness. Such a coordinated effort can reduce disparities in global AI capabilities and facilitate more equitable participation in the technological advancements of the future.

5. Policy Implications

The analysis underscores the critical necessity of strategic AI investments to bridge regional and continental disparities in AI adoption and development:

Infrastructure Development: The advancement of digital infrastructure is essential to fostering AI adoption, particularly in regions such as Sub-Saharan Africa, parts of Asia, and Oceania. Investments in high-speed broadband networks, mobile connectivity, and reliable electricity access are foundational prerequisites for AI-driven initiatives. Addressing these infrastructural deficiencies is fundamental to enabling equitable technological development, allowing underserved regions to actively participate in the AI revolution. In particular, enhancing last-mile connectivity, supporting public-private partnerships, and ensuring affordable internet access are key strategies that can significantly expand the reach of digital infrastructure. Investments in renewable energy sources to support reliable electricity access can also create synergies with sustainability goals, making AI adoption more environmentally friendly and resilient.

Government Policy and AI Strategies: Governments must formulate and implement comprehensive national AI strategies that create an enabling environment for AI development. These strategies should encompass ethical guidelines, regulatory frameworks for responsible AI, and incentives to stimulate private-sector engagement. Effective policy interventions must also prioritize data privacy, encourage open data initiatives, and develop adaptive regulatory frameworks to mitigate risks while fostering innovation. Such strategies are crucial to ensure that AI adoption contributes meaningfully to sustainable and inclusive development. Moreover, cross-border collaborations and regional alliances can further strengthen AI capabilities, enabling smaller nations to benefit from shared resources and knowledge. Governments should also focus on establishing AI regulatory sandboxes that allow controlled experimentation, helping refine AI policies while safeguarding public interests.

Skill Development: Building AI-related skills and capabilities is imperative for sustaining AI growth, especially in low- and middle-income countries. Policymakers should prioritize integrating AI and data science education into national curricula at all educational levels, alongside promoting vocational and lifelong learning programs. Establishing targeted training initiatives to enhance AI literacy is vital for cultivating a workforce capable of effectively engaging with AI technologies, ensuring that AI investments generate broad-based societal benefits. Additionally, partnerships with industry leaders and academic institutions can help in creating specialized AI training centers and mentorship programs, which are crucial for bridging the skill gap. Efforts to increase gender diversity in AI-related fields should also be a focal point to ensure that AI development benefits from a wide range of perspectives and talents, thereby promoting more inclusive growth.

The AIIPI reveals substantial regional disparities in AI investment attractiveness, with Europe and North America emerging as leaders, whereas regions such as Africa and parts of Asia significantly lag. To foster equitable global AI development, collaboration among policymakers, international organizations, and private investors is imperative. Addressing foundational barriers—including inadequate infrastructure, insufficient policy frameworks, and skill deficits—will be instrumental in promoting inclusive AI growth, which is essential for achieving the Sustainable Development Goals by 2030. Engaging in multilateral initiatives that bring together diverse stakeholders can facilitate the sharing of best practices and accelerate progress across lagging regions.

Policymakers should focus on enhancing digital infrastructure, governance, and research ecosystems. Given the influence of factors such as population size and research output on AI attractiveness, policies designed to expand AI-focused education and strengthen research initiatives can markedly enhance a country's potential for AI investments. Expanding funding opportunities for AI research and fostering collaborations between academia and industry are crucial components of this strategy. The AIIPI serves as a crucial tool for identifying strategic opportunities to cultivate robust AI ecosystems globally, thereby guiding stakeholders toward interventions that foster equitable and sustainable development. Furthermore, targeted interventions in areas such as AI ethics, societal impact assessments, and international regulatory harmonization can ensure that AI growth aligns with broader human development objectives, ultimately contributing to a fair and just global AI landscape.

Further research could explore time-varying weights for indicators, income group-specific weights, and non-linear relationships to better understand evolving dynamics.

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Annex 1 Data sources and information on indicators

Table 2. Data sources and information on indicators

Indicators	Description of Indicators	Primary Source	Source of the source
Government Promotion of Investment in Emerging Technologies	Average answer to survey questions concerning the extent to which different governments foster investments in five types of emerging technology.	Oxford Insights Government AI Readiness Index 2023 AI Readiness Index - Oxford Insights	Network Readiness Index (Portulans Institute) Network Readiness Index – Benchmarking the Future of the Network Economy
Graduates in STEM or computer science	Percentage of graduates in STEM from tertiary education for both sexes. The following indicator has been retrieved from a larger database regarding the distribution of tertiary graduates by field of study.		UNESCO UIS Statistics (unesco.org)
Statistical Capacity	The SPI framework assesses the maturity and performance of national statistical systems in five key areas, called pillars. The five pillars are: Data use, Data Services, Data Products, Data Sources, Data Infrastructure.		World Bank Statistical Performance Indicators (worldbank.org)

Data Privacy and Protection Law	Classification of data-related regulation by country.Each classification has been assigned to a percentage corresponding to the relative advancement of the country in terms of the establishment of accountable administrative bodies for data protection: • 0%: no specific law • 50%: partially adequate • 100% : data protection law(s) • 100%: EU or EEA member country • 100%: Independent authority and law(s).	CNIL (French Data Protection Authority) Data protection around the world | CNIL	CNIL (French Data Protection Authority) Data protection around the world | CNIL
Telecommunications Infrastructure Index	This index - ranging from 0 to 1- is a composite indicator composed of four indicators: the percentage of internet users, the Mobile-cellular subscriptions per 100 inhabitants, the active mobile-broadband subscriptions, the Fixed broadband subscriptions per 100 inhabitants.	UN E-Government Knowledgebase Data Center (un.org)	International Telecommunications Union Statistics (itu.int)

Human Capital Index (HCI)	The HCI - ranging from 0 to 1 - is a weighted average composite of four components retrieved from the UNESCO-UIS : Adult literacy (25%), Gross enrolment ratio (25%), Expected years of schooling (25), Mean years of schooling (25%).		World Bank https://data.worldbank.org/indicator/HD.HCI.OVRL
GSMA Connectivity Index	The Mobile Connectivity Index measures the performance of 173 countries against the key enablers of mobile internet adoption.	Oxford Insights Government AI Readiness Index 2023 AI Readiness Index - Oxford Insights	GSMA Mobile Connectivity Index 2024 – GSMA Mobile Connectivity Index
Access to Electricity	The percentage of population with access to electricity. Electrification data are collected from industry, national surveys and international sources.	World Bank World Development Indicators via DBnomics: Access to electricity (% of population) WB/WDI | DBnomics	World Bank https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS

Government Effectiveness	Reflects the perception of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. It ranges from approximately -2.5 to 2.5.	World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)	World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)
Control of Corruption	Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. It ranges from approximately -2.5 to 2.5.		World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)

Rule of Law	Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. It ranges from approximately -2.5 to 2.5.		World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)
Regulatory Quality	Reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. It ranges from approximately -2.5 to 2.5.		World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)
Political Stability	Measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. It ranges from approximately -2.5 to 2.5.		World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)

Voice and Accountability	Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. It ranges from approximately -2.5 to 2.5.		World Bank Worldwide Governance Indicators Home | Worldwide Governance Indicators (worldbank.org)
GDP per Capita PPP	Provides per capita values for gross domestic product (GDP) expressed in current international dollars converted by purchasing power parity (PPP) conversion factor.	World Bank https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD	World Bank https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD
GDP per Capita (current $)	GDP per capita is gross domestic product divided by midyear population.	World bank GDP per capita (current US$)	World Bank https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
Population	This indicator is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates.	World Bank https://data.worldbank.org/indicator/SP.POP.TOTL	World Bank https://data.worldbank.org/indicator/SP.POP.TOTL

Number of articles	The number of AI articles published by authors from the country over the past decade. Author countries are inferred from where their organizations are located over a dataset of more than 260 million scholarly articles.	Emerging Technology Observatory Country Activity Tracker: Artificial Intelligence Country Activity Tracker: Artificial Intelligence (eto.tech)	The Merged Academic Corpus (MAC) is a dataset that is not publicly available but is composed of data from Clarivate's Web of Science platform, The Lens, The arXiv platform, Papers with Code, Semantic Scholar and OpenAlex.
Percentage of articles with international collaboration	Percentage of articles per country lists authors from organizations located in more than one country over a dataset of more than 260 million scholarly articles.	Emerging Technology Observatory Country Activity Tracker: Artificial Intelligence Country Activity Tracker: Artificial Intelligence (eto.tech)	The Merged Academic Corpus (MAC) is a dataset that is not publicly available but is composed of data from Clarivate's Web of Science platform, The Lens, The arXiv platform, Papers with Code, Semantic Scholar and OpenAlex.
Patents granted	Patents granted counts the number of grants per country for over 360,000 AI-related patent families, which are groups of patent documents related to the same invention.	Emerging Technology Observatory Country Activity Tracker: Artificial Intelligence Country Activity Tracker: Artificial Intelligence (eto.tech)	CAT uses patent data from 1790 Analytics, PATSTAT, and The Lens.
Percentage of patent growth	Growth in granted patents from 2018 to 2021 shows the evolution of granted patents from 2018 to 2021.	Emerging Technology Observatory Country Activity Tracker: Artificial Intelligence Country Activity Tracker: Artificial Intelligence (eto.tech)	CAT uses patent data from 1790 Analytics, PATSTAT, and The Lens.

Number of incoming investments	Counts the number of incoming investments for each country per year.		Crunchbase (commercial datasets) Crunchbase: Discover innovative companies and the people behind them

Annex 2 Descriptive Statistics of Unscaled Data, and Table of Weights from the Best Model

Table 3. Minimum and Maximum Values of unscaled data

Variable	Min	Max
AI.Strategy	0	100
Access.to.electricity.data	32	100
GSMA.Connectivity.Index	33.803	93.477
Data.Privacy.and.Protection.Score	0	100
Log.GDP.per.capita.PPP	7.332	11.894
government.effectiveness	-1.889	2.285
Human.Capital.Index	0.204	1
Telecommunication.Infrastructure.Index	0	1
Political.stability	-2.475	1.468
Population	47642	1417173173
Voice.and.accountability	-1.778	1.775
Number.of.articles	4	575258
%.articles.with.international.collaboration	3	132672
Statistical.Data.Capacity	34.8	93.6

Example Calculation

For the Population variable, where the minimum population is 47,642 and the maximum is 1,417,173,173, a country with a population of 41,128,771 would have a scaled value of approximately 2.90. The scaled value is computed as:

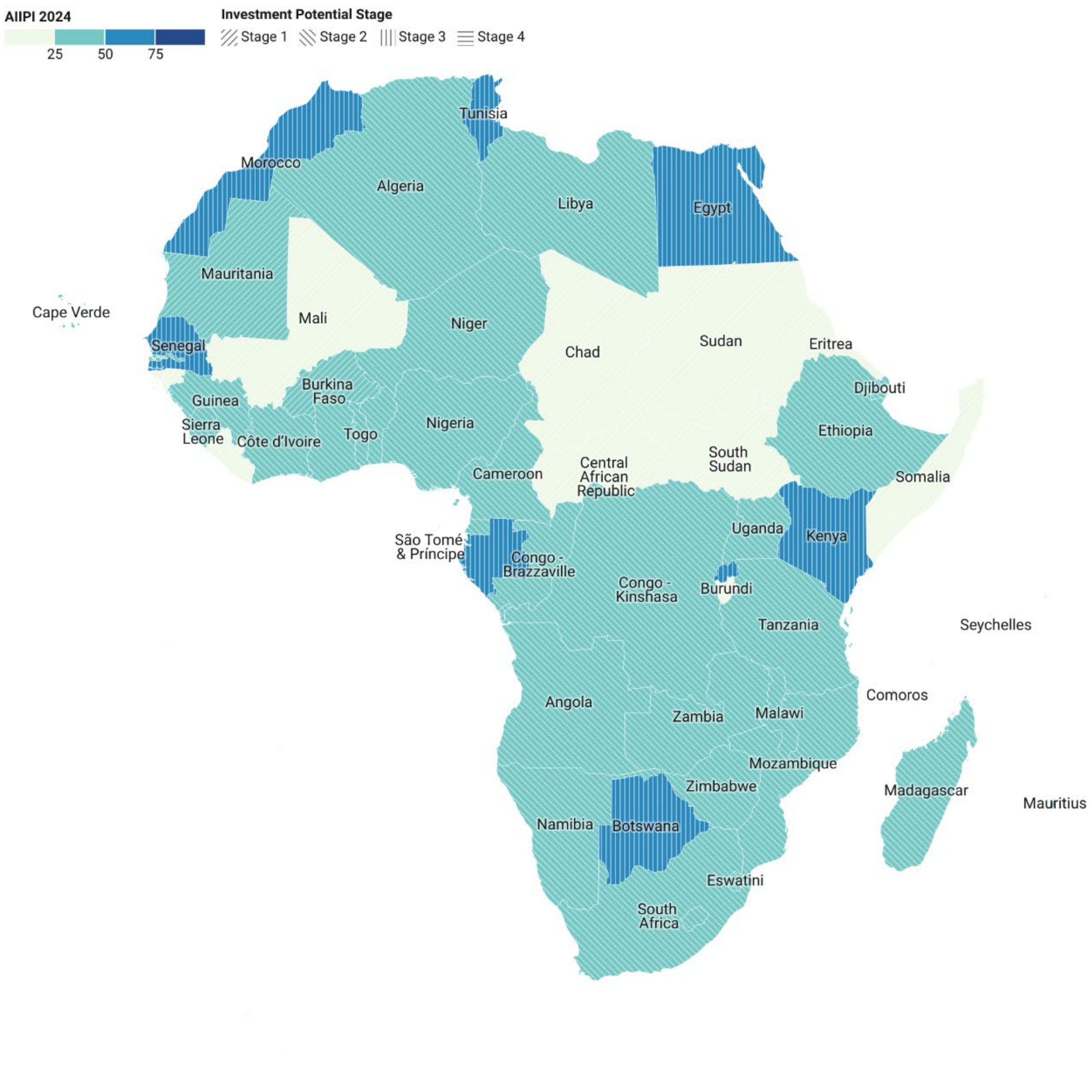
$$\mathit{Scaled\ Population} = (41{,}128{,}771 - 47{,}642) / (1{,}417{,}173{,}173 - 47{,}642) \times 100 = 2.90$$

Table 4. Random Forest Variable Importance Weights

Variable	Random Forest Variable Importance Weights
Population	0.202523637
Number of Articles	0.129985020
GSMA Connectivity Index	0.126591159
Statistical Data Capacity	0.113244356
Government Effectiveness	0.109207093
Political Stability	0.104082874
Human Capital Index	0.072933423
Log GDP per Capita PPP	0.050017260
Voice and Accountability	0.047246416
Data Privacy and Protection Score	0.023939106
Telecommunication Infrastructure Index	0.012127162
Access to Electricity Data	0.006549224
AI Strategy	0.001553270

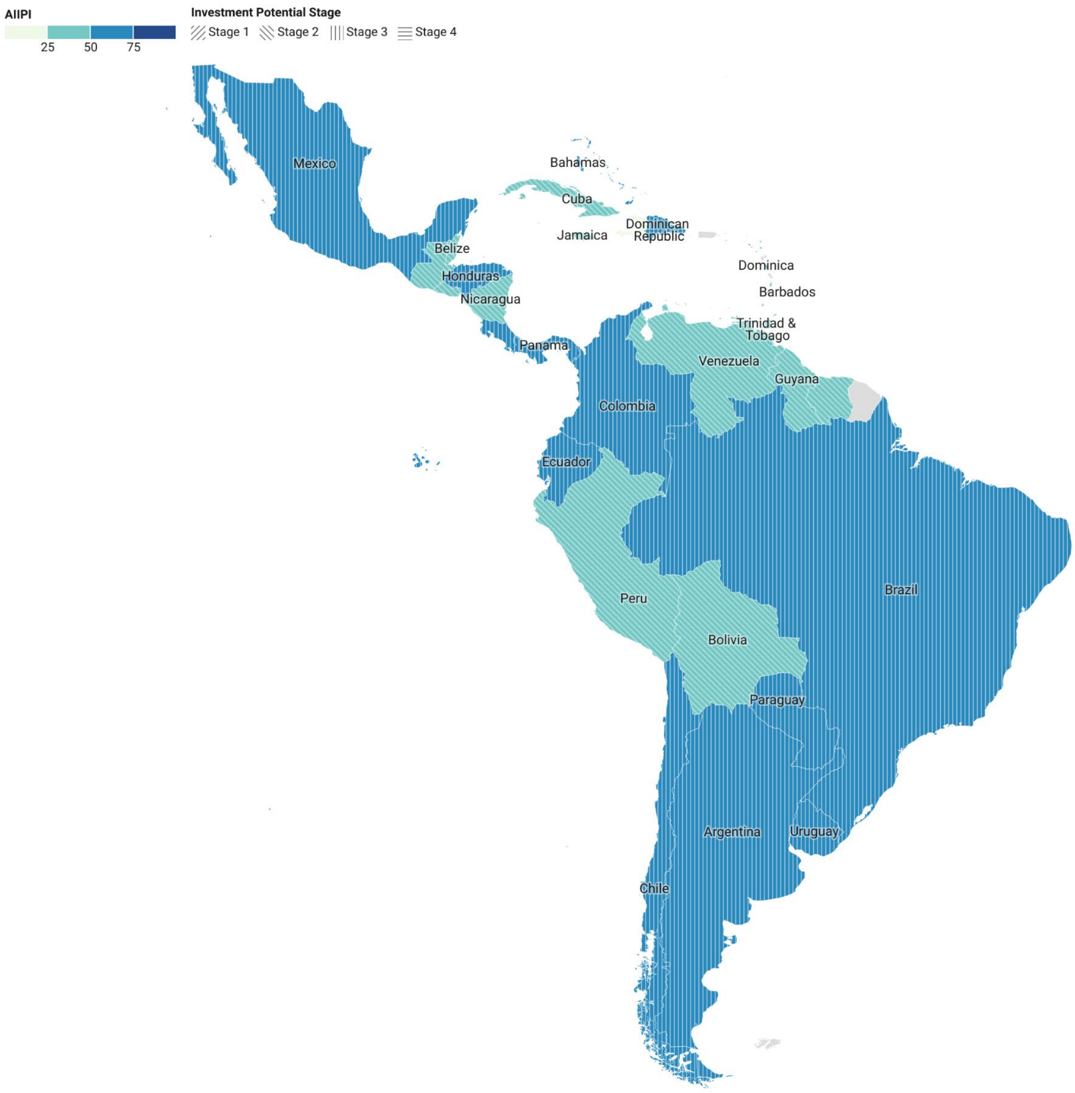
Annex 3 Geographical Maps on AI Investment Potential Index

Map 2. AI Investment Potential Index in Africa



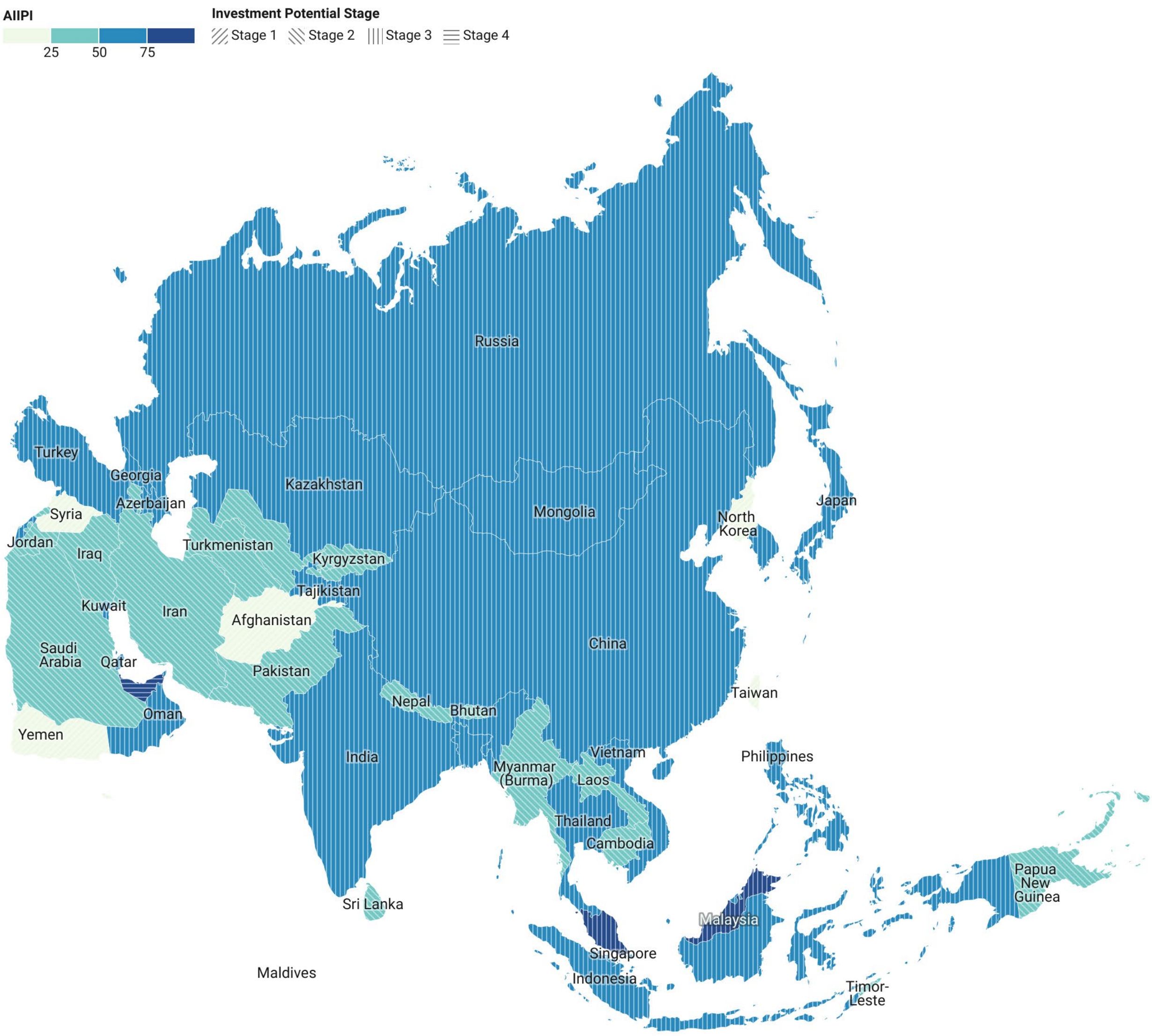
Map: Agence française de développement (AFD) • Created with Datawrapper

Map 3. AI Investment Potential Index in Latin America



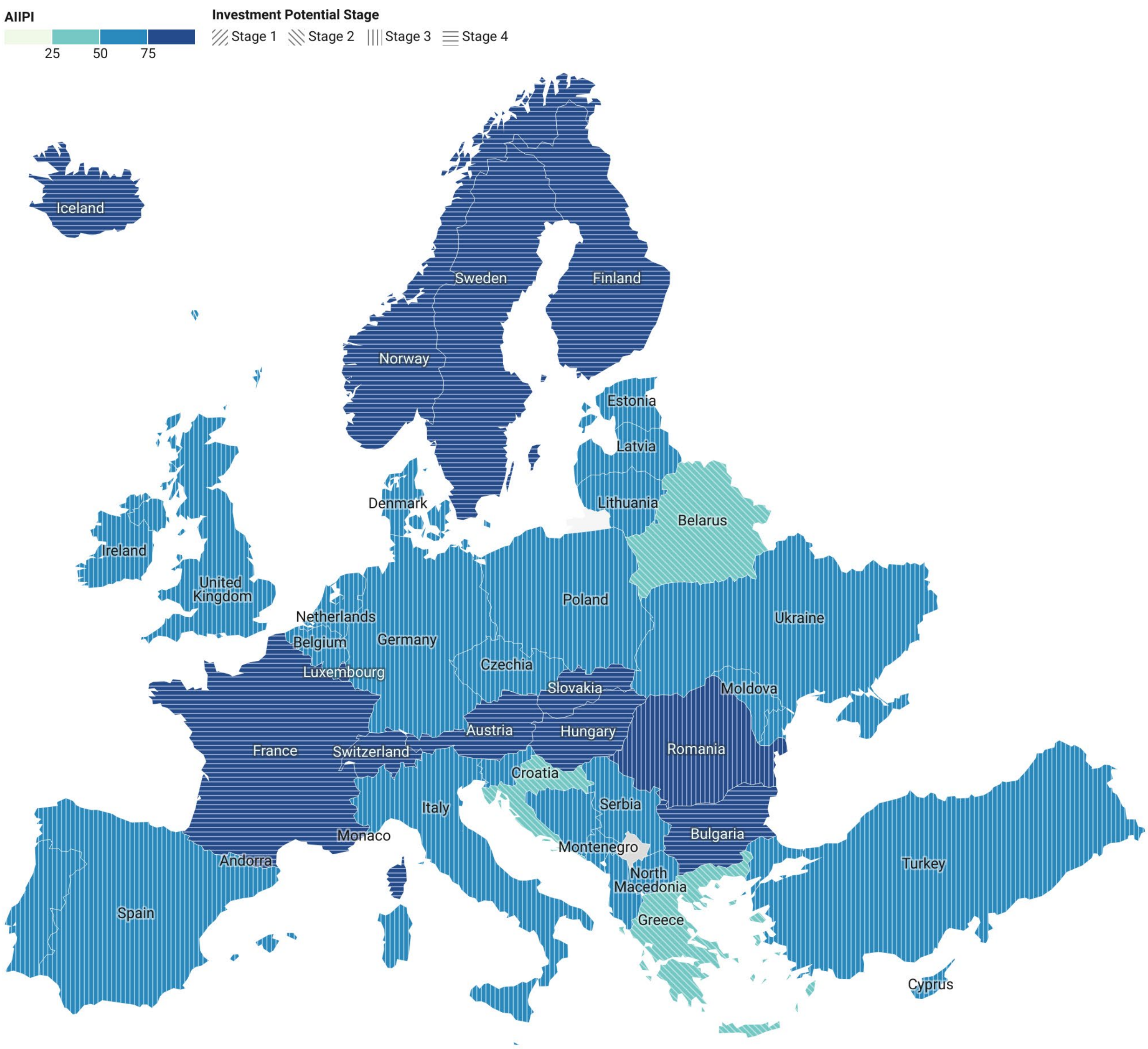
Map: Agence française de développement (AFD) • Created with Datawrapper

Map 4. AI Investment Potential Index in Asia



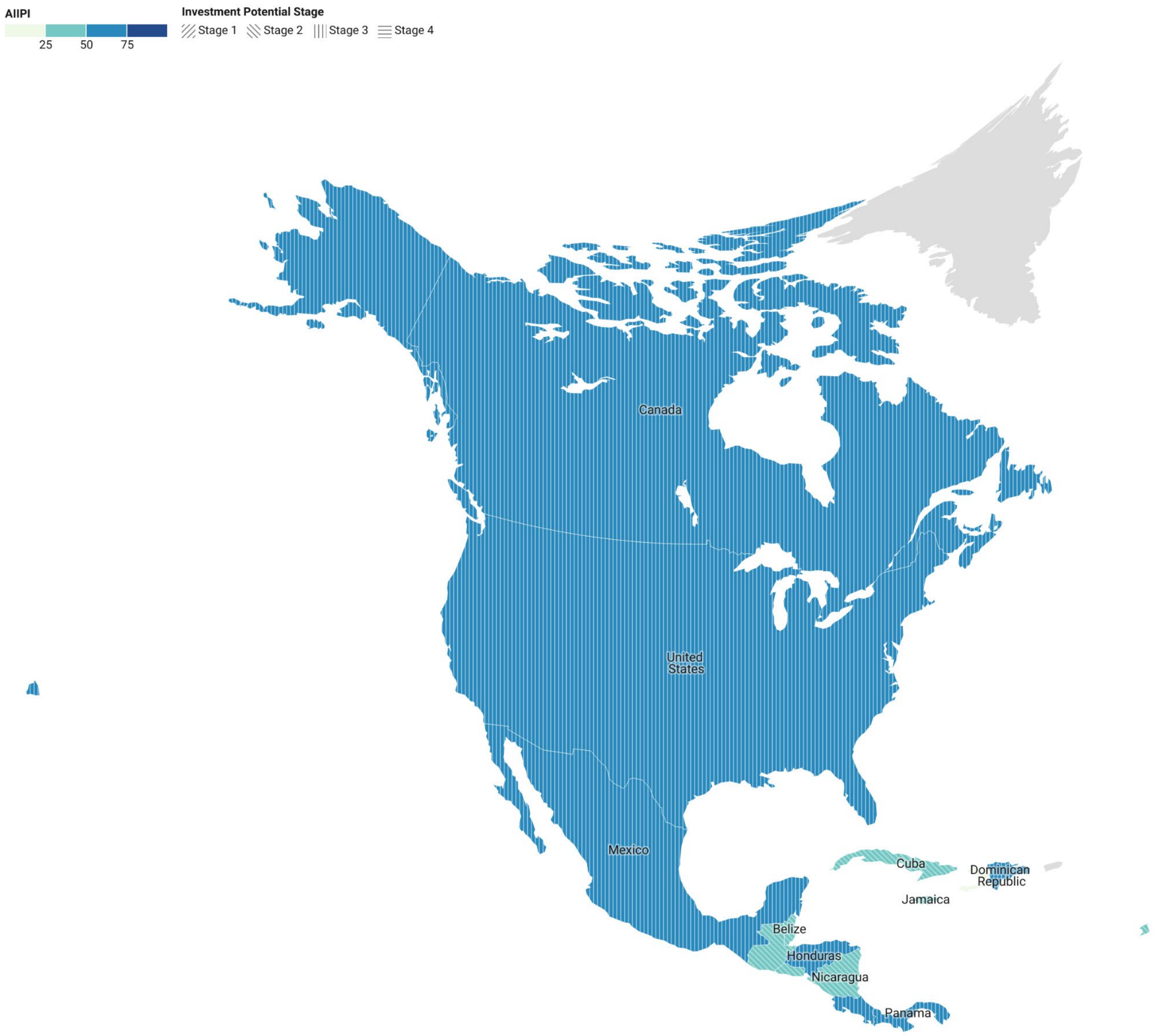
Map: Agence française de développement (AFD) • Created with Datawrapper

Map 5. AI Investment Potential Index in Europe



Map: Agence française de développement (AFD) • Created with Datawrapper

Map 6. AI Investment Potential Index in North America



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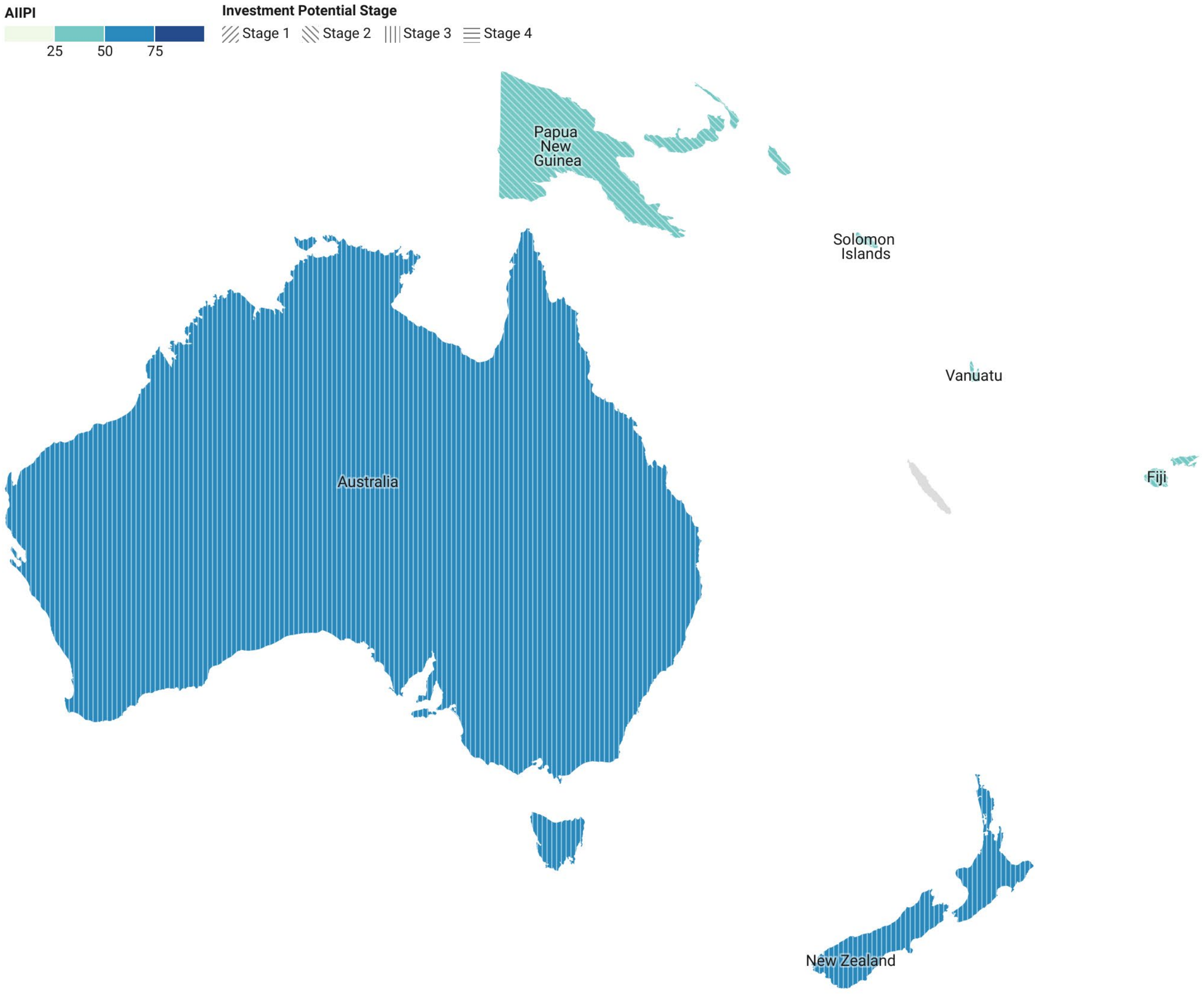
Map 7. AI Investment Potential Index in Oceania



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Annex 4 Table Comparison of AI Investment Potential Index (AIIPI) with Existing Indices

Table 5. Comparison of AIIPI, IMF AI preparedness and Oxford Insights

Aspect	IMF AI Preparedness Index (AIPI)	AI Investment Potential Index (AIIPI)	Oxford Insights Government AI Readiness Index
Definition & Objectives	Measures AI preparedness across 174 countries, focusing on digital infrastructure, human capital, technological innovation, and regulatory frameworks. Designed to offer a broad view of AI readiness.	Identifies global AI investment potential among 193 countries, integrating AI readiness with socio-economic, governance, and macroeconomic factors to promote inclusive and sustainable growth.	Evaluates 181 governments' readiness to adopt AI, focusing on digital capacity, governance, and innovation ecosystems. Aims to guide government AI strategies.
Methodology	Normalizes sub-indicators to a 0-1 scale and aggregates using simple averaging and then average of first principal components (PCA) of each dimension. All indicators are treated equally, potentially missing complex interactions.	Utilizes advanced machine learning techniques (Elastic Net, Random Forests) to identify variable importance to predict AI incoming investments. The weights obtained based on variable importance. An entropy-based weighting is also used to assign importance variable indicators. The best evaluation model and composite index is selected.	Uses a composite index methodology, with equal weighting of indicators. Data is normalized through min-max scaling.

Principal Indicators Used	1. Digital Infrastructure: Internet access, secure internet servers, broadband subscriptions, etc. 2. Human Capital and Labor Market Policies: Education levels, digital skills, STEM graduates, internal labor market productivity, flexibility of wage determination, etc. 3. Technological Innovation and Economic Integration: R&D spending, AI-related patents, scientific publications, mean tariff rate, Free movement of capital and people, etc. 4. Regulatory and Ethical Frameworks: Government effectiveness, legal adaptability.	1. AI Readiness: Telecommunication infrastructure, human capital, mobile connectivity. 2. Socio-economic Factors: Population, Governance, political stability and government effectiveness 3. Macroeconomic Outlook: GDP, access to electricity; purchasing power 4. Innovation Capacity: AI research articles, data capacity, etc.	1. Government AI Strategy: Vision, Digital capacity, governance and ethics, adaptability. 2. Technology Sector: Technology sector maturity, innovation capacity, human capital. 3. Data and Infrastructure: Infrastructure, data availability, data representativeness.

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