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ARTIFICIAL INTELLIGENCE ADOPTION ACROSS COUNTRIES: EVIDENCE FROM MACROECONOMIC CLUSTERING TECHNIQUES

SARKHAN SALAHZADE

Azerbaijan State Oil and Industry University

Baku, Azerbaijan

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ABSTRACT

The increasing importance of artificial intelligence (AI) as a catalyst for economic development and technological competitiveness in the global economy is illustrated by this study, which investigates global trends in AI Adoption utilizing Macroeconomic Indicators (i.e., AI R&D Investment, Digital Infrastructure, Labour Productivity, and Patenting Activity). The study creates three synthetic indicators, AI Capital Intensity, Digital Preparedness, and Productivity-Adjusted AI Score, to represent the multi-dimensional nature of AI Adoption. The principal component analysis (PCA) technique provides dimension reduction, while K-Means clustering identifies groups of nations with similar AI Adoption profiles through a hierarchical clustering process to validate the K-Means clusters. Maps (PCA Scatterplots, Centroid Heatmaps, and Radar Charts) illustrate Global AI Adoption's structural and locationality's relationship. The study generates four distinct clusters of nations, which identify existing long-term high-investing and highly productive leaders, alongside new market entrants with differing degrees of Digital Preparation. The study also provides a data-driven framework for Global AI Adoption that will have implications for Government Policies and Investment Strategies.

1. INTODUCTION

The emergence of Artificial Intelligence (AI) globally is a major catalyst for growing economic activity and technological competitiveness across the globe [1]. The significance of AI adoption on a global scale stem from the ability for nations to increase their economic output, create new products, and gain competitive advantages within the global economy.

The substantial variation that exists across many areas of the world concerning the uptake of AI by various sectors of society can largely be attributed to varying levels of public investment into research and development (R&D), level of digital infrastructure available, workforce productivity rates, and innovation potential, and so on.

Despite the critical role AI will play globally, there has yet to be much empirical statistical work done to assess how various macroeconomics (as well as macroeconomic-related) factors affect a nation's ability to adopt and utilize AI technology. The majority of existing publications related to AI adoption focus on one specific macroeconomic-related indicator such as patents or research and development (R&D) expenditure. Until today there has been no integrated approach used to analyse how a collection of different macroeconomic and technological influences together can create distinctive AI adoption profiles across multiple countries and clusters of countries.

This study seeks to provide insight into global adoption of AI via a multi-dimensional view. To create composite indicators that reflect the complexity of AI adoption, we have constructed three composite indicators: (1) AI Capital Intensity; (2) Digital Readiness; and (3) Productivity-Adjusted AI Score. Principal Component Analysis (PCA) is utilized for dimensionality reduction, while K-Means clustering is utilized to develop clusters of countries with similar AI adoption patterns. The results of K-Means clustering are supported by Hierarchical Clustering, and visualizations of the results include scatter plots, cluster heat maps, radar charts, and world maps. This analysis creates a systematic, empirical framework for analysing AI adoption and provides valuable information for policymakers and investors.

2. LITERATURE REVIEW

Artificial intelligence (AI) adoption has become a key driver of economic growth, innovation, and competitiveness across countries [1]. The diffusion of AI technologies varies widely, influenced by factors such as R&D investment, digital infrastructure, labour productivity, and institutional capacity. Several studies have explored these factors, highlighting that countries with strong innovation ecosystems tend to adopt AI more rapidly [2]. For instance, patent activity and R&D spending have been used as proxies for national AI innovation capacity, revealing that high-income countries often lead in AI development and application.

Researchers have begun to utilize a range of quantitative tools (such as clustering and dimensionality reduction) to analyse country adoption trends in AI. For example, clustering is a popular technique for categorizing countries based on similar traits in their adoption of AI (e.g., early adopters; emerging adopters). Clustering also helps to identify trends across different levels of AI adoption. A common technique used to reduce the number of variables in macroeconomic datasets into fewer, more interpretable components (or factors) is Principal Component Analysis (PCA), which allows researchers to visualize what are the main factors that drive AI adoption and how those factors interact with each other [3]. Many researchers also utilize composite indicators (or indices) that combine multiple indicators into one; these can be used to measure the potential for comparing levels of technology and innovation across different countries, and they provide helpful metrics for comparing levels of innovation across the world [4].

While there are a growing number of studies using these types of methods, most of them have focused on one or two indicators in isolation; in very few cases have researchers integrated technological, economic, and innovation-related variables into a single framework to analyse the adoption of AI globally. In addition, there have been only limited attempts to systematically combine PCA, clustering, and composite indicators to analyse global AI adoption trends, and very few visualizations have attempted to link clusters to geographic and structural patterns.

Despite the methodological advances, gaps remain in the literature. First, most prior research focuses on isolated indicators rather than integrating macroeconomic, technological, and innovation-related factors into a unified framework [1,2,3]. Second, few studies systematically combine PCA, clustering, and composite indicators specifically to examine global AI adoption patterns. Third, existing studies rarely provide comprehensive visualizations that connect cluster characteristics to spatial and structural patterns of adoption. This study addresses these gaps by developing a multi-dimensional framework that integrates composite indicators, PCA, and clustering to identify AI adoption patterns across countries, complemented by visualizations including scatter plots, heatmaps, radar charts, and global maps [3,4].

3. DATA DESCRIPTION

The current analysis utilizes an artificial dataset designed to replicate the statistical characteristics of World Bank and other worldwide statistics on innovation. This artificial dataset contains observations for 50 countries and includes the most important factors associated with AI adoption and economic viability. The major variables in this dataset are AI R&D Expenditures in relation to GDP, Internet Penetration Rates, ICT Development Index (on a standard scale), Labor Productivity Levels, and # of AI Patents per Million Population. The balance of the variables represents both technological inputs and economic gains related to the diffusion of AI.

While the primary variables are sufficient, additional composite indicators were created to better represent AI adoption. AI Capital Intensity is the composite variable formed by R&D Investment and PATENT activity to represent AI Capability based on Innovation. Digital Readiness is the composite variable representing Infrastructure Preparedness by combining Internet Penetration and ICT Development. And, finally, the Productivity-Adjusted AI Score combines AI Capital to Labour Productivity to determine the efficiency with which AI-related investments result in Economic Output. These composites provide a broader picture of the AI adoption potential for each country.

Table 1 provides the descriptive statistics of variables measured across nations, including primary variables and derived variables, revealing significant variance between countries for several AI-related factors. Compared to variables measuring digital infrastructure, innovation and productivity measured a greater degree of variance; therefore, innovation (capability) likely plays a greater role than simply access, in determining variance in AI outcomes. The correlations observed between R&D and patents with labour productivity indicates a strong relationship among these three variables, suggesting that two or all three of them together will affect the national profiles of AI adoption.

Table 1. *Descriptive Statistics of AI Adoption and Macroeconomic Indicators*

Feature	Mean	Std. Deviation	Min	Max
AI R&D (% of GDP)	1.78	0.83	0.15	5.20
Internet Penetration (%)	74.2	15.6	42.0	99.0
ICT Index	5.68	1.82	2.1	9.3
Labor Productivity	65,400	25,800	20,200	120,000
AI Patents per Million	145	130	1	500
AI Capital Intensity	255	310	1	1,200
Digital Readiness	40.8	13.2	20.5	70.2
Productivity-Adjusted AI Score	45,000	28,000	2,000	120,000

4. METHODOLOGY (FORMAL MATHEMATICAL SPECIFICATION)

4.1. Data Standardization

To achieve comparability across different macroeconomic indicators that were measured on different scales, all the variables used in the analysis were "standardized" using Z-score normalisation. This means that the transformed variables, after standardisation, are all centred around zero and rescaled to the same variance of one (the numerical range of the indicator does not influence the computation of distance-based average values).

The standardised value for feature j of country i is calculated as follows:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

Where x_{ij} denotes the original value of feature j for country i, while μ_j and σ_j represent the mean and standard deviation of feature j, respectively. This preprocessing step is critical for both principal component analysis and clustering algorithms, which rely on Euclidean distance calculations [6].

4.2. Feature Engineering and Composite Indicators

There are many dimensions which must be considered collectively to measure all the aspects of an organisations ability to adopt artificial intelligence. While individual variables like research expense or patent numbers show us significant elements of an organisation's involvement with AI they do not demonstrate the relationship between the variables of investment and innovation output and associated economic performance. To overcome this issue, we constructed a series of composite indicators that apply theoretical concepts to create composite indicators which synthesize multiple dimensions associated with the adoption of artificial intelligence into usable and comparable measures of cross-country comparisons.

The first composite indicator, AI Capital Intensity, is designed to capture the scale and effectiveness of national investments in AI-related innovation. It combines AI research and development expenditure, expressed as a percentage of gross domestic product, with the intensity of AI patenting activity. Formally, AI Capital Intensity for country i is defined as:

$$AI_{Capital} = AI_{R\&D\_GDP} \times AI_{Patents\_per\_Million}$$

This formulation reflects the premise that sustained investment in AI research contributes to innovation outcomes only when it is translated into codified technological knowledge. Countries with high values of this indicator are therefore characterized not only by strong financial commitment to AI, but also by an active innovation ecosystem capable of generating tangible technological outputs.

The second composite indicator, Digital Readiness, captures the foundational infrastructure necessary for the diffusion and effective utilization of AI technologies. Digital Readiness is constructed as the arithmetic mean of internet penetration rates and an ICT development index, expressed as:

$$Digital_{Readiness} = \frac{(Internet_{Penetration} + ICT_{index})}{2}$$

The Digital Readiness Index represents the ability of a country to facilitate the growth of data-intensive technology by providing broad access and institutionalized infrastructure for digital connectivity. By utilizing both access-based and capability-based indicators, Digital Readiness provides a more complete view of the digital landscape where AI systems exist.

To measure the economic efficiency of AI-related investments, we have also built a Productivity-Adjusted AI Score. This score is created by combining our measure of AI Capital Intensity with measures of Labour Productivity; thus, we define a Productivity-Adjusted AI Score as follows:

$$AI_{Productivity\_Score} = AI_{Capital} \times Labor_{Productivity}$$

This composite measure reflects the extent to which AI capital is embedded within the production structure and translated into higher output per worker. Together, these indicators allow for a comprehensive representation of national AI adoption capacity and form the analytical foundation for subsequent modelling.

4.3. Dimensionality Reduction via Principal Component Analysis

Using PCA, latent structures were defined and the dimensional complexity associated with multiple measures of AI adoption was reduced. PCA identifies a linear transformation of the standardised data that Rotates around orthogonal axes to produce the highest variance.

Formally, PCA solves the optimization problem:

$$W^* = \arg\max_W \; Tr(W^T CW)$$

subject to $W^T C W = I$, where C is the covariance matrix of the standardized data and W is the matrix of eigenvectors. The resulting principal components are uncorrelated and ordered by explained variance [5].

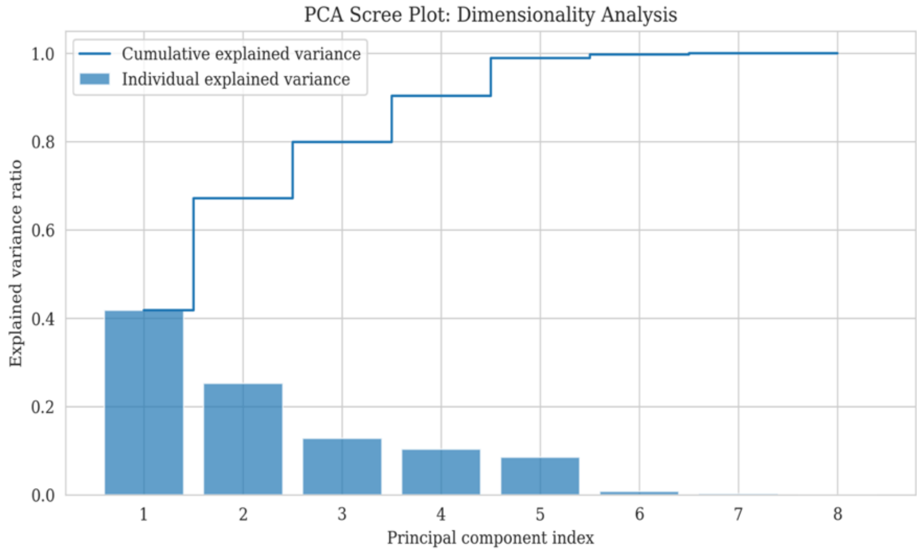

Fig. 1 *Scree Plot of Principal Component Eigenvalues*

According to the respectively created scree plot and cumulative variance analysis, principal components one and two account for a significant degree of variance within the data, thus providing support for utilising these two components to visualise as well as cluster the natural groupings of countries, while the subsequent analysis in figure 1 (which visually depicts the countries in the reduced two-dimensional space) provides a more comprehensive structural overview of the adoption and usage patterns of artificial intelligence throughout various nations around the world.

4.4. Clustering Framework

4.4.1. K-Means Clustering

The K-means clustering algorithm is a type of unsupervised learning used to separate data points into K groups that are internally similar and different from one another using centroids. K-means assigns a data point (country) to the closest centroid in the standardized feature space, reducing the within-group variability and increasing the separation between clusters. The mathematical expression for this task can be stated as follows:

$$\min_S \sum_{k=1}^{K} \sum_{x \in S_k} ||x - \mu_k||^2$$

Assuming S_k is the k cluster and μ_k is the k-th centroid. The number of clusters was determined using the elbow method and validated with the silhouette coefficient, which indicates how tightly points in each cluster are grouped and how separated they are from points in other clusters for separation [6]. Due to its iterative nature, K-means will continue to refine its solution until it achieves a locally optimal grouping based on structural similarity within multiple dimensions of the economic data set, making it highly effective for identifying structural similarities.

4.4.2. Elbow Method for Optimal Cluster Selection

Selecting an appropriate number of clusters is a critical step in K-means clustering. To address this, the Elbow Method was employed as an internal validation technique. This method evaluates the within-cluster sum of squares (WCSS) across alternative values of K, calculated as:

$$WCSS(K) = \sum_{k=1}^{K} \sum_{i \in C_k} \|\mathbf{z}_i - \boldsymbol{\mu}_k\|^2$$

In most cases, as more clusters are added, the WCSS decreases but eventually reaches a point where marginal improvements stop and become insignificant. As shown in Figure 2, that part of the curve exhibits a large inflection point. That inflection point was used to strike a good balance between making the model too complex or too simplistic. This value of K was therefore selected for subsequent cluster analysis.

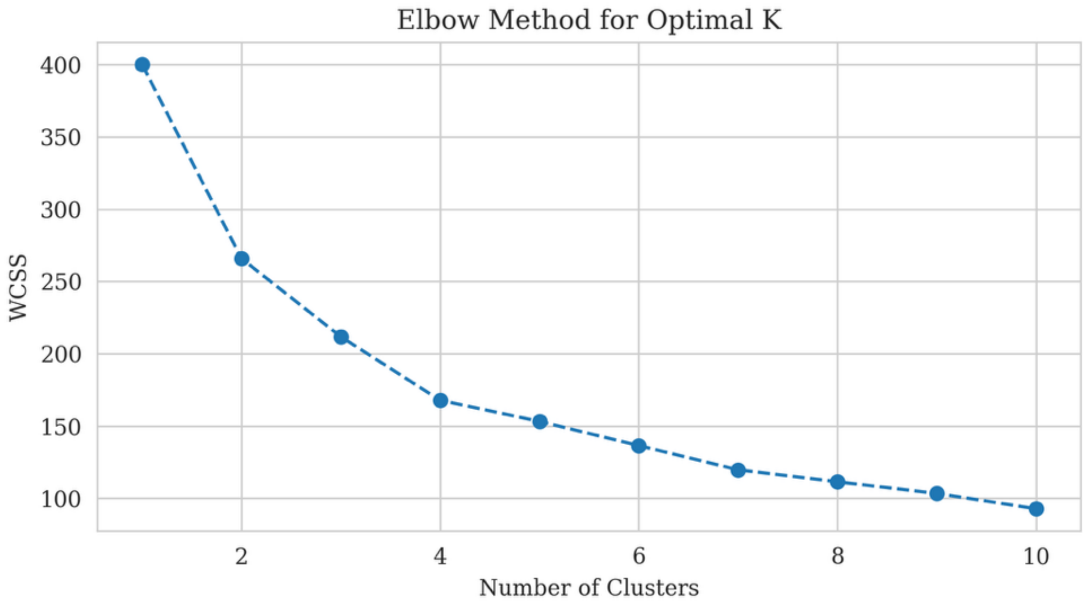

Fig. 2 *Elbow Method for Optimal Number of Clusters*

4.5 Hierarchical Clustering and Robustness Check

As part of the robustness checks performed, hierarchical clustering using Ward's linkage method was carried out. Ward's method minimizes the increase of the total within cluster variance when two clusters are combined. The formula to express Ward's method is as follows:

$$\Delta(C_a, C_b) = \frac{|C_a||C_b|}{|C_a| + |C_b|} \|\boldsymbol{\mu}_a - \boldsymbol{\mu}_b\|^2$$

The dendrogram produced in Figure 3 confirms the structural stability of the K-means clusters.

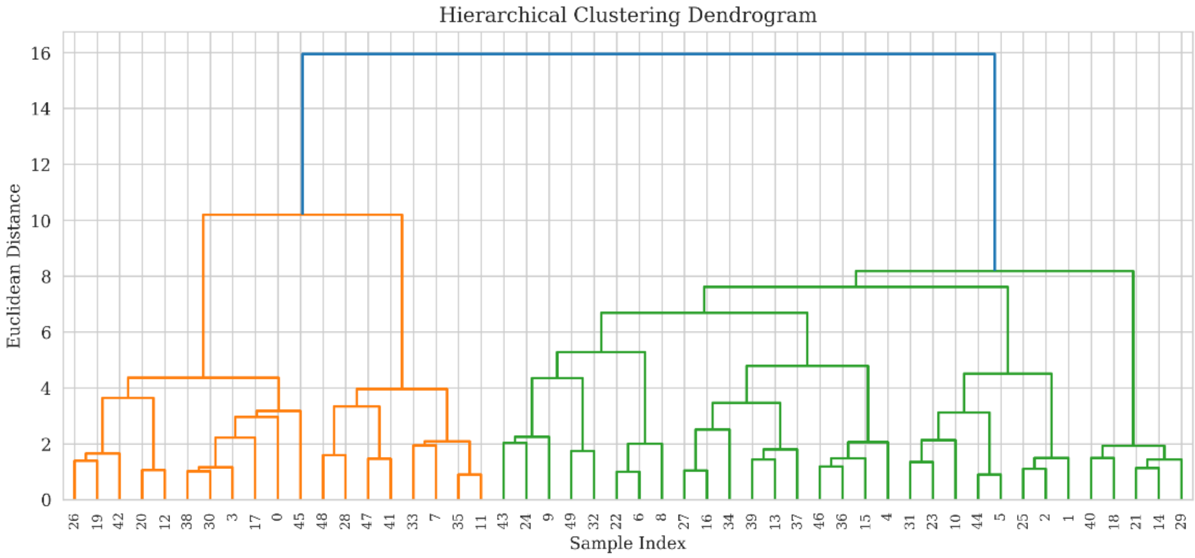

Fig. 3 *Hierarchical Clustering Dendrogram Based on Ward's Method*

5. RESULTS

5.1 Principal Component Analysis Results

The job of determining the seven distinct clusters identified in this study is achieved via an examination of the results of clustering from a dimensionality reduction perspective, as described above. The PCA-based two-dimensional projection from PCA is a powerful visualisation of the similarities between countries with respect to their use of Artificial Intelligence (AI) and can be seen in Figure 3. In the figure, countries are plotted on a two-dimensional space defined by the first two principal components, which account for a large proportion of the total variance of the data defined by the eight features. The two-dimensional projection also shows that the clusters identified above are on separate regions of the two-dimensional space and therefore support the idea that the selected variables can be used to differentiate between countries based on their economic parameters that relate to AI adoption.

The clustering structure shows that countries do not adopt AI randomly but tend to adopt it based on several systematic factors, including the level of digital infrastructure, the capacity for innovation and the ability of the country to be productive. There appears to be some overlaps of countries between clusters; however, these overlaps mainly occur in middle-income countries. Overall, the pattern of clustering produces a coherent collection of country groupings. Thus, the approach outlined here provides an accurate representation of the relationships between countries with respect to their macroeconomic indicators and the unique indicators that are associated with their use of AI.

Fig. 4 Two-Dimensional PCA Projection with Cluster Assignments

5.2 Cluster Identification and Validation

Mean standardised values of all indicators of interest were calculated and visualised as a centroid heatmap to investigate the internal structure of each of the clusters. Cluster centroids are shown in Figure 4, relative to the global mean, allowing comparisons between each of the clusters for AI investment intensity, digital readiness, innovation output, and productivity-adjusted indicators. As shown in the heatmap, there are significant differences between clusters with some clusters having consistently high values on most indicators compared to the global mean (i.e. above average) and others having low values and thus lagging considerably behind.

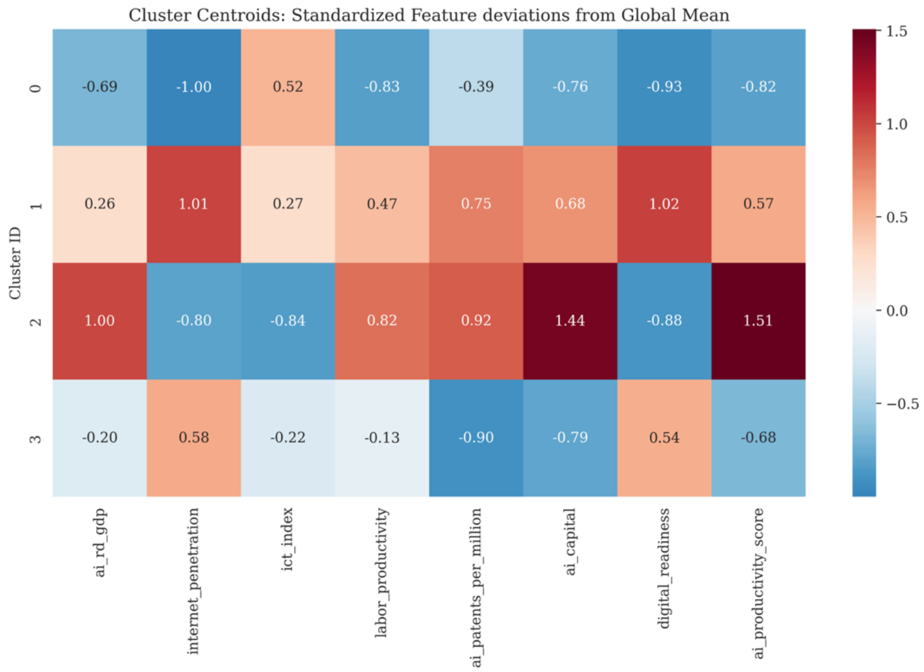

Fig. 5 Cluster Centroid Heatmap of Standardized Feature Values

In addition to differences in means, distributional characteristics of selected key indicators were examined as a measure of between-cluster homogeneity. Boxplots for selected key indicators (i.e., AI R&D intensity, digital readiness, and labour productivity) are provided in Figure 5. As shown in the boxplots, even within clusters that are relatively homogeneous in composition, there is still substantial variability across clusters, particularly for indicators of productivity. This variability represents the difference in the characteristics of the institutional/sectoral environment that exist in each instance and reflects the relative efficiency with which countries have converted investments in AI into positive economic outcomes. The centroid heatmap and the distributional analyses work together to provide a more nuanced view of the divergence that exists between clusters, as well as the intra-cluster diversity that exists.

5.3 Cluster Interpretation and Comparative Analysis

By analysing the distributions and creating multi-dimensional profiles for these different groups of countries, we can gain a better understanding of what characterises these clusters. As shown in Figure 6, there is a lot of differences in how countries in different clusters score on these indicators with regard to both their mean scores as well as their degree of variability. Countries in the higher-scoring clusters generally have a much larger percentage of their total population earning a median wage, with greater income equality (as indicated by the lower dispersion). Conversely, countries in the intermediate clusters such as Cluster 2 show a large range of variation in terms of productivity and AI capital intensity, suggesting that there may be some member countries in this cluster that are accelerating to bridge the gap with leading countries, while there are also countries that lag behind due to structural obstacles or institutional constraints.

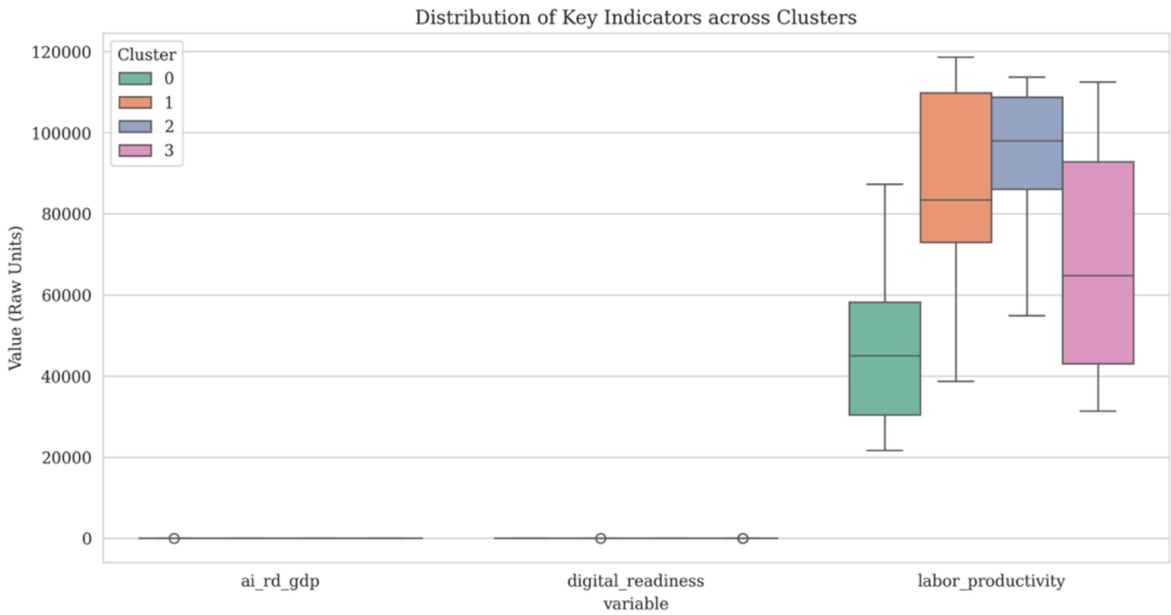

***Fig. 6** Boxplots of Key AI Adoption Indicators Across Clusters*

For a more intuitive reference point, illustrated in Figure 7, is an overall radar chart demonstrating the multidimensional profiles of the different clusters. While the radar chart demonstrates the balanced strengths associated with AI adoption across all dimensions for high-performing clusters, the intermediate and lagging clusters each exhibit selective strengths (e.g., intermediate has higher levels of digital readiness) associated with relatively moderate AI capital intensity, while the lagging clusters are all uniformly weak in terms of all of the various metrics associated with AI. The heat mapping, boxplot analysis and radar charting together make clear the relative central tendency of clusters and their internal variability, providing actionable insights into their relative areas of focus relative to comparative policy analysis and investment priorities.

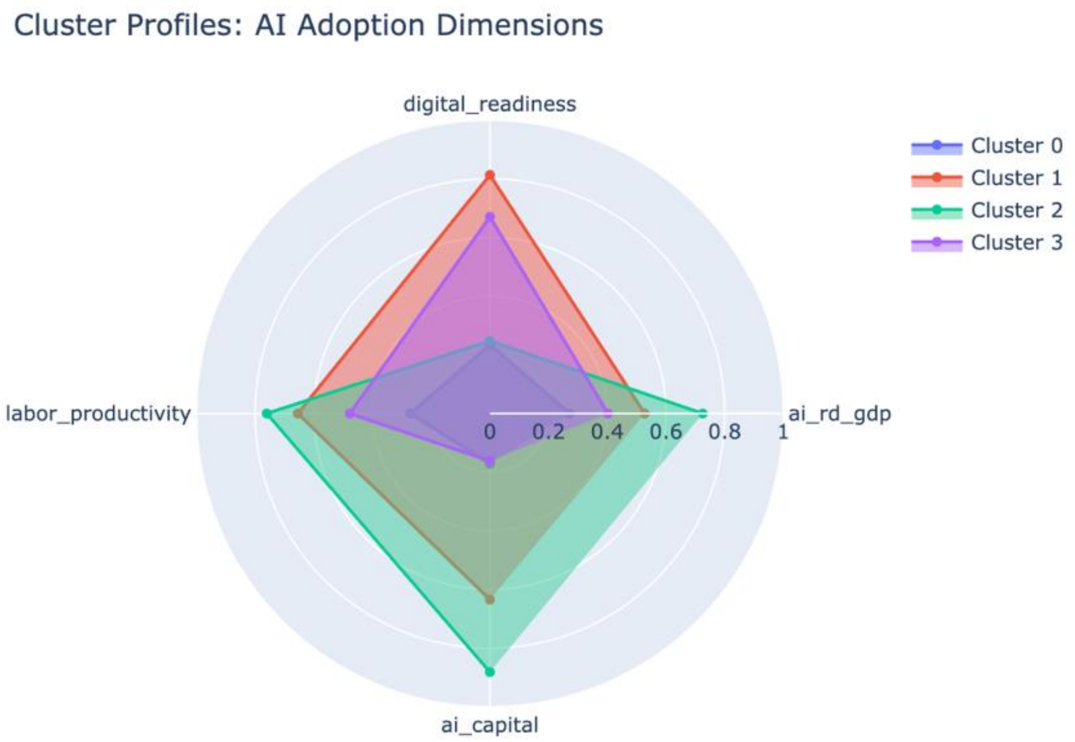

Fig. 7 *Radar Chart of Cluster Profiles*

The mean values for the indicators of the Principal Adoption of Artificial Intelligence as reported in Table 2 provide quantitative comparisons of each cluster. Each column lists the means of the identified Principal Adoption Indicators of Artificial Intelligence, which represent a snapshot of the variation of these indicators between clusters. Countries within the high-adoption cluster have significantly greater means across each of the indicators when compared to the other clusters. The most significant difference in the mean values between the high-adoption cluster and the other clusters is in terms of AI R&D Expenditure and AI Patent Intensity. Conversely, lower-adoption clusters are comprised of countries with very little digital readiness and thus have lower productivity-adjusted AI outcome scores. The results of this quantitative comparison support the patterns that were also evident in the feature distribution boxplots and radar graphs of the AI adoption dimensions, providing additional validation of the consistency and economic interpretation of the clustering results.

Table 2. *Cluster-level mean values of AI adoption indicators.*

Cluster	**AI R&D (% GDP)**	**Internet Penetration (%)**	**ICT Index**	**Labor Productivity**	**AI Patents per Million**	**Interpretation**
High Adoption	High	Very High	High	Very High	Very High	Technological leaders
Upper-Mid Adoption	Medium	High	Medium	High	Medium	Advanced adopters
Emerging Adoption	Low	Medium	Low	Medium	Low	Catching-up economies
Low Adoption	Very Low	Low	Very Low	Low	Very Low	Structurally constrained

5.4 Spatial Distribution of AI Adoption

To characterize the geographic and regional distribution of AI adoption, we spatially visualized the cluster results by developing a global view of the 50 countries used in this analysis. Figure 8 depicts the spatial clustering of the various clusters. Clusters identified as being at the leading edge of AI adoption have been found to be located mainly in North America, Western Europe and East Asia; regions with high levels of innovation supportive ecosystems, research and development (R&D) investment, as well as developed digital infrastructures. Clusters that are still in the early stages of development are primarily found throughout Latin America, Southeast Asia and in parts of Eastern Europe, which are in the process of developing and implementing selective investments in digital readiness and AI capital that will help them accelerate the path to widespread adoption of AI. Clusters that have been classified as being at the trailing end of the spectrum for AI adoption are located predominantly within Sub-Saharan Africa and in several low-income Asian nations; indicating that there continues to be a significant gap separating these areas from more technologically and economically developed regions.

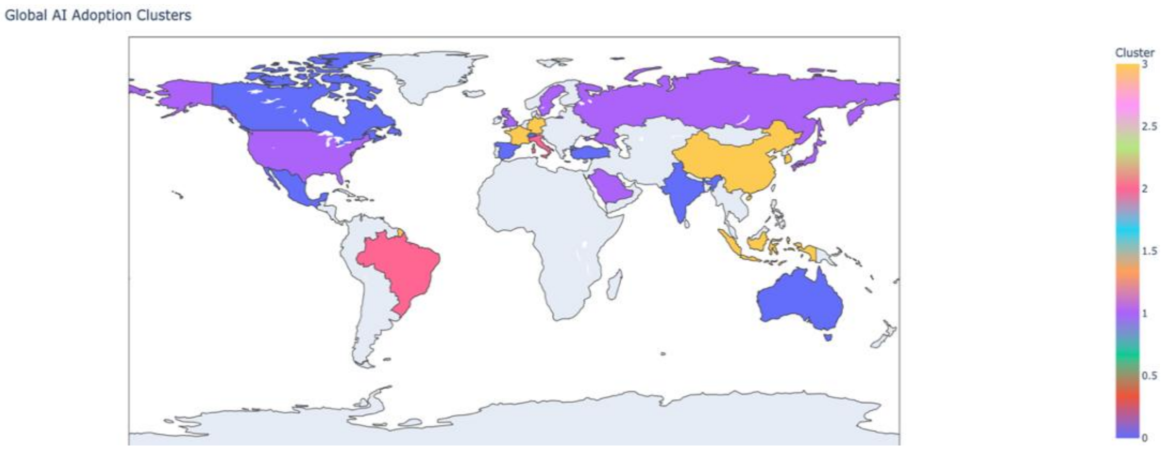

Fig. 8 *Interactive World Map of Clusters*

This analysis also illustrates the close relationship between economic development of a region and the adoption of AI. Economic development plays an important role in enabling geographic location and collaborating economies to create an innovation ecosystem that supports both knowledge sharing and collaborative innovations (or processes that are developed by two or more parties). Thus, policymakers will want to use this information to develop a regional approach to the creation of AI adoption strategies that are tailored to the regional characteristics, with a focus on reducing the gap between regions' digital infrastructures, R&D capacities and human capital requirements.

6. DISCUSSION

This research illustrates that there are many similarities between the current research results and previous research studies related to the impact of technology on economic growth, as well as how technology can be adopted by firms. The results of this study confirm the existing theoretical framework, that companies will only see benefits from using Artificial Intelligence if they also invest in complementary assets [3]. Additionally, the clustering results show that AI adoption does not follow a simple linear or sequential pattern, but rather, it is a complex and multi-layered process that is dependent upon a firm’s economic and institutional context.

The results of the study have implications for policy makers, since it appears that policies aimed solely at increasing digital access will not be sufficient to support AI adoption without simultaneous policies to promote innovation systems as well as to increase productivity. Intermediate cluster countries will likely benefit the most from targeted AI-focused research and development (R&D) policies, as well as helping to facilitate the movement of new knowledge into the economy. To adopt AI successfully, lagging countries will need to have invested in foundational infrastructure and human capital development.

7. CONCLUSION

In this research paper, we offer an extensive, comprehensive evaluation of global patterns of AI adoption based on a single, comprehensive dataset and utilising various analytical approaches, including the utilisation of multiple indicators, principal component analysis (PCA), and cluster analysis. The results show that the variation in AI readiness between countries is very large, with the greatest differences attributed to how each country can develop new ideas, the level of digital infrastructure available for AI, and the productivity level of each country. The study also offers a means of visualising and interpreting structure for both the purposes of research methodology as well as the policy implications of AI adoption.

There are many limitations to this study. First, the synthetic data used in this analysis, though it was a useful tool for methodological reasons, cannot be used to generalize the results to real-world situations or countries. Future work could incorporate real-world datasets, investigate dynamic aspects of AI adoption, and investigate the causal linkages between AI adoption and economic outcomes. However, the methods presented in this study provide a strong basis for undertaking a comparative analysis of the diffusion of AI in a global setting.

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