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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

GLOBAL AI CLUSTERS: STRUCTURAL PATTERNS IN SKILLS, TALENT, AND ENTREPRENEURSHIP

KÜRESEL YAPAY ZEKÂ KÜMELERİ: YETENEK, BECERİLER VE GİRİŞİMCİLİKTEKİ YAPISAL EĞİLİMLER

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Abstract

Artificial intelligence (AI) acts as a strategic catalyst for digital transformation, fostering innovation and redefining labor market dynamics. However, empirical studies that quantitatively compare and classify the extent and nature of cross-country differences in AI talent capacities remain limited. This study aims to address the existing gap in the literature by analyzing the presence of significant clusters among countries based on five strategic AI-related indicators: Hiring, Skill Penetration, Talent Concentration, Talent Migration, and Newly Funded AI Companies. Using 2024 data from 47 countries, a K-means clustering analysis was performed, with the optimal number of clusters identified as four through the elbow method. The results reveal significant structural and multidimensional divergences in AI capacity across countries. Based on the K-means clustering analysis, nations were categorized into four distinct clusters according to the five core AI indicators. The findings indicate that cross-country differences are influenced not only by individual indicators but also by the balance and overall structure among these indicators. The study also offers policy recommendations to support the AI-related development of countries. This research represents one of the few empirical studies that comparatively analyze the multidimensional positioning of countries in AI, providing policymakers with a vital reference point for prioritization and strategic planning.

Keywords: Artificial Intelligence, K-means Clustering, Cross-country Comparison

JEL Classification: M16, M21, M48

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Öz

Yapay zekâ (YZ), ülkelerin dijital dönüşüm kapasitesini, inovasyon potansiyelini ve işgücü piyasalarını yeniden şekillendiren stratejik bir alandır. Ancak ülkelerin YZ alanındaki yetenek temelli kapasite farklarının hangi göstergelerle ne düzeyde ayrıştığı, nicel olarak karşılaştırmaya ve sınıflandırmaya yönelik ampirik çalışmalar sınırlıdır. Bu çalışma, bu literatür boşluğunu doldurmayı amaçlayarak, YZ'ye ilişkin beş stratejik gösterge üzerinden ülkeler arasında anlamlı kümeler olup olmadığını analiz etmektedir: İşe alım oranı, beceri yayılımı, yetenek yoğunluğu, net yetenek göçü ve fonlanan YZ girişim sayısı. 2024 dönemine ait 47 ülkenin verilerini kullanarak K-ortalamalar algoritmasıyla kümeleme analizi gerçekleştirilmiş, küme sayısı dirsek yöntemiyle dört olarak belirlenmiştir. Sonuçlar, ülkeler arasında YZ kapasitesi bakımından yapısal, istatistiksel olarak anlamlı ve çok boyutlu ayrışmalar olduğunu göstermektedir. Çalışmada gerçekleştirilen K-ortalamalar kümeleme analizi sonucunda ülkeler, yapay zekâya ilişkin beş temel göstergeye göre dört anlamlı kümeye ayrılmıştır. Bulgular, ülkeler arasındaki farkların yalnızca tekil göstergelere değil, göstergeler arasındaki dengeye ve bütüncül yapıya bağlı olarak şekillendiğini ortaya koymaktadır. Çalışma ayrıca politika önerilerinde bulunmaktadır. Bu çalışma, YZ alanında ülkelerin çok boyutlu konumlarını karşılaştırmalı olarak analiz eden nadir ampirik çalışmalardan biridir ve politika yapıcılar için önceliklendirme ve stratejik planlama açısından önemli bir referans noktası sunmaktadır.

Anahtar Kelimeler: Yapay Zekâ, K-ortalama Kümeleme, Ülkeler Arası Karşılaştırma
JEL Sınıflandırması: M16, M21, M48

1. Introduction

Artificial intelligence (AI) technologies, which encompass five subfields machine learning, deep learning, natural language processing, computer vision, and explainable AI are fundamentally transforming business operations today and in the future. AI has the capability to analyze extensive datasets and accurately predict outcomes across various scenarios with remarkable speed. These technologies contribute not only to solving complex challenges but also to enhancing the efficiency of operational processes across a diverse array of products and services. In many instances, AI systems can execute specific tasks more quickly, accurately, and efficiently than humans, occasionally exceeding human capabilities. Scholars at the intersection of economics, management, and data analytics are increasingly investigating, through the lens of AI, which countries are likely to lead this transformation and the potential consequences of such advancements. This technology, which originated in the mid-20th century with Alan Turing, has rapidly evolved to become one of the defining technologies of the 21st century, emerging as a strategic priority for nations, corporations, and global investors.

Factors such as Hiring, Skill Penetration, Talent Concentration, Talent Migration, and the number of Newly Funded AI Companies are essential in assessing a country's competitive advantage in the artificial intelligence (AI) sector. However, the intricate interrelationships among these indicators require a modeling approach that transcends simple univariate analyses. The primary objective of this study is to classify countries within a multivariate framework by examining their similarities based on the indicators of Hiring, Skill Penetration, Talent Concentration, Talent Migration, and Newly Funded AI Companies. To achieve this, a K-means clustering model was developed, utilizing these five core indicators that reflect various dimensions of AI. This methodology aims to create homogeneous groups of countries based on their levels of advancement in the AI field.

Significant disparities exist among countries regarding AI-related investment and human capital capacities. However, the systematic categorization of these differences and the extent to which such classifications can inform strategic planning have not been thoroughly investigated. In this context, classifying countries based on comparable AI performance indicators is essential for both comparative analysis and regional collaboration. This study specifically aims to conduct a systematic analysis of multivariate AI indicators at the country level. To achieve this, countries with similar structural characteristics were clustered using the K-means method. Based on the findings, the study seeks to provide an analytical framework of countries' AI competencies, offering valuable insights for policymakers and decision-makers.

This research offers substantial contributions to the literature at both methodological and applied levels. Firstly, the implementation of an effective machine learning technique, specifically the K-means algorithm, within the complex and multidimensional domain of artificial intelligence establishes a benchmark for similar studies in the field of quantitative methods. Secondly, the analysis of real-time labor market dynamics utilizing data from large-scale digital platforms, such as LinkedIn, facilitates the inference of national-level skill and investment capacities. Furthermore, this study provides insights that can inform concrete policy recommendations, thereby supporting the development of more robust strategies for talent cultivation and retention.

This study is founded on several key assumptions. First, it is posited that the chosen indicators adequately reflect the performance of countries in the field of artificial intelligence (AI). Additionally, it is assumed that data sourced from LinkedIn is comprehensive and reliable enough to facilitate cross-country comparisons. Furthermore, it is assumed that the K-means algorithm utilized is an appropriate method for similarity-based classification, and that the resulting cluster structures effectively represent the AI competencies of the countries analyzed.

2. Literature Review

Countries aspiring to achieve leadership in the AI sector must focus on the development of public policies, allocation of financial resources, enhancement of human capital and collaborative networks, promotion of public awareness, and integration of ethical and legal considerations (Al-Marzouqi & Arabi, 2024; Pillai & Sivathanu, 2020). Given its high value added potential and ability to drive systemic transformation, AI has been positioned as a strategic element in the development policies of numerous nations, leading to the creation of national strategy documents and institutional frameworks. The strategic priorities regarding AI governance in China, the European Union, and the United States are influenced not only by technical factors but also by their respective political regimes and cultural norms (Wang et al., 2025). China's focus on research and application aligns with its state-driven, technology-oriented development model; the EU prioritizes social impact within a framework of democratic values; while the US emphasizes the regulatory role of the state within its market-based system (Djeffal et al., 2022; Guenduez & Mettler, 2023). Although these entities share similar narratives regarding risks, their policy implementations differ significantly. However, a common trend is emerging in their focus on strengthening institutional capacities to mitigate technological risks and protect fundamental rights (Li et al., 2023; Wu et al., 2020). This suggests that while global AI governance may be shaped by universal principles, it retains significant contextual differences in practice.

As of 2021, the United States' AI research and development expenditures amounted to USD 52.9 billion, while China's private sector-based AI R&D investments reached USD 17.2 billion approximately one-third of the US level (Zhang et al., 2021). By 2024, private sector investment in AI in the United States had surged to USD 109.1 billion, roughly twelve times China's USD 9.3 billion and twenty-four times the United Kingdom's USD 4.5 billion. In the same year, US-based institutions developed 40 major AI models, compared to China's 15 and Europe's mere 3, highlighting America's clear technological leadership and global dominance in this field (Maslej et al., 2025).

In contrast to China, the adoption of AI technologies in business processes remains limited across many Asian countries. In Indonesia (24.6%), Thailand (17.1%), Singapore (9.9%), Malaysia (8.1%), and India (22%), only a minority of enterprises have integrated AI applications into their operations (Pillai & Sivathanu, 2020). These findings indicate that AI adoption is still in its early stages in the region. Researchers have attributed these low adoption rates to a lack of technological awareness, inadequate educational infrastructure, and challenges in organizational adaptation (Chen et al., 2022; Hossin et al., 2021; Islam et al., 2024; Md. Aftab Uddin, 2021; Pillai & Sivathanu, 2020). Particularly in areas such as human resources, where potential benefits are clear, practical implementation remains limited (Hossin et al., 2021). In this context, competition among countries fueled by AI is becoming more pronounced, particularly regarding investment levels and technological output. AI investments and production capacity are set to be crucial factors in determining global leadership in the future.

In developing countries, the dissemination of AI skills among individuals is essential for economic development and digital equity. AI technologies possess the potential to bridge the digital divide by empowering non-technical users to perform a range of tasks (Bejaković & Mrnjavac, 2020; Choi, 2021). In this context, AI-powered platforms facilitate the acquisition of fundamental digital skills and enhance learning processes through tools such as language training and online guidance (Jiao et al., 2023). Moreover, to promote the societal adoption of AI skills, it is advisable to enrich educational systems with AI-focused content and expand professional development programs (Leoste et al., 2021; B. D. Lund & Wang, 2023).

Comprehensive and long term policy initiatives are essential to ensure the equitable dissemination of AI capabilities beyond specific hubs and across diverse geographical and socio-economic regions (Lund et al., 2021). In developing countries, deficiencies in infrastructure, limited access to resources, and inadequate educational systems impede the full realization of technological advancements, negatively impacting talent development (Ernst et al., 2019; Houde et al., 2020). The concentration of AI capabilities within specific regions and sectors may constitute a significant structural barrier limiting the participation of developing countries in global AI activities. The migration of skilled personnel in the AI field toward countries that provide enhanced research opportunities, financial support, and improved career prospects intensifies the issue of Talent Migration in developing nations. To address this challenge, it is essential to strengthen AI policies, restructure educational systems to prioritize AI-related skills, and further develop mechanisms that support entrepreneurship (Lund et al., 2023; Schiff, 2022). Retaining AI talent domestically necessitates the establishment of an innovation framework based on collaborations among universities, research centers, and the private sector. Otherwise, developing countries' competitiveness of developing countries in the AI arena and hinder their ability to retain their already limited human capital (Mannuru et al., 2023). In summary, without significant investments in AI technologies from both public and private sectors, the retention of skilled personnel and the support of local AI initiatives will be increasingly impractical.

Generative AI tools enhance employability by improving language proficiency and digital literacy while streamlining employers' candidate evaluation processes (Lund et al., 2023). Furthermore, the emergence of new job roles, such as prompt engineering, suggests that hiring strategies are evolving in tandem with technological advancements (White et al., 2023). The transformation driven by AI technologies in the labor market has the potential to reshape hiring processes significantly. Specifically, the automation facilitated by AI-based tools in resume preparation, portfolio creation, and application material enhancement increases the efficiency of the hiring process. This development indicates that AI-driven employment opportunities have diversified, not only in quality but also in variety

The opportunities offered by AI technologies have given rise to new business models. These models can provide companies with strategic advantages, particularly in areas such as productivity, decision support systems, and customer experience (Bang et al., 2023; Houde et al., 2020). However, in developing countries, ensuring the sustainability of such initiatives requires the implementation of multidimensional support mechanisms, including infrastructure investments, regulatory frameworks, and public–private partnerships (Lund et al., 2023). The number of newly established AI companies and their commercialisation capacity constitute strategic indicators that directly influence a country's position in the AI-driven transformation process. In other words, the establishment and financing of AI-based start-ups are considered significant indicators of technological advancement and economic growth.

2.1. Theoretical Framework: Artificial Intelligence and Economic Development Theories

Building on the insights provided in the literature review, it is essential to situate this study within a broader theoretical context. While prior research emphasizes national strategies, investments, and institutional frameworks in shaping artificial intelligence (AI) development, linking these dynamics to established economic development theories enhances the explanatory power of the current analysis. The five AI indicators employed in this study Hiring, Skill Penetration, Talent Concentration, Talent Migration, and Funded AI Companies can be understood not only as empirical measures but also as reflections of fundamental mechanisms in development economics.

Human Capital Theory

Human capital theory, pioneered by Becker, posits that economic growth is driven by the quality and skills of the labor force (Gary S. Becker, 1994). The indicators of Skill Penetration and Talent Concentration directly reflect countries' investments in human capital. High penetration of

AI-related skills and concentrated pools of expertise demonstrate the extent to which nations are cultivating knowledge-based growth.

Endogenous Growth Theory

Endogenous growth models, developed by Romer and Lucas, emphasize technological innovation, knowledge spillovers, and increasing returns to scale as key drivers of long-term growth (Varga & Schalk, 2004). In this study, Funded AI Companies and Hiring align with this framework, as they represent entrepreneurial activity and the expansion of the AI workforce that sustain innovation-driven growth.

Structuralist Development Approaches

Structuralist perspectives, represented by Prebisch and Hirschman, argue that development unfolds through imbalances and structural dependencies (Fischer, 2015). The indicator of Talent Migration illustrates such asymmetries, as developing countries often face structural disadvantages due to brain drain. This pattern reinforces global inequalities in AI capacity and demonstrates how structural dependence undermines the ability of less developed economies to retain and utilize their skilled workforce.

Cluster Theory and National Innovation Systems

Porter's cluster theory and the national innovation systems framework highlight the role of geographic and sectoral agglomerations in fostering innovation and competitiveness (Lundvall, 2016). The indicators of Funded AI Companies and Talent Concentration reflect the clustering of AI start-ups and innovation hubs, which serve as engines of regional competitive advantage. These dynamics emphasize that AI development is embedded in broader innovation ecosystems that support entrepreneurship, collaboration, and commercialization.

Migration and Brain Drain Literature

The development economics literature on brain drain underscores how skilled migration restricts growth in developing countries while reinforcing competitive advantages in advanced economies. The indicator of Talent Migration, particularly in smaller countries such as Luxembourg, Estonia, and Cyprus, exemplifies what Schiff (2022) describes as the "knowledge transfer gap," whereby external expertise is not sufficiently diffused into the local workforce. This undermines the potential for building sustainable, knowledge-based economies

3. Methodology

3.1. Research Design

Prior to conducting the clustering analysis, a series of preliminary analyses were executed on five AI indicators across 47 countries with complete observations. Initially, a correlation analysis was performed to investigate the relationships among the variables. Subsequently, box-plot analyses were utilized to identify outliers, which revealed significant outlying values in certain variables. To address this concern, a logarithmic transformation was first applied to the 'Funded AI Companies' variable, which exhibited the highest outlier values. Following this, Winsorization was implemented across all variables to mitigate the influence of extreme values. To eliminate scale discrepancies and ensure comparability among variables, all variables were standardized. These procedures were undertaken to prepare the dataset for clustering analysis. Within the K-means framework, the optimal number of clusters was determined using the Elbow, Silhouette, and Gap statistics. Analysis of variance (ANOVA) was subsequently employed to assess whether statistically significant differences existed among the identified clusters. Based on the strengths and weaknesses of each cluster, policy recommendations were formulated, offering specific guidance for notable countries within each cluster. All analyses were conducted using the R programming language.

3.2. Variables

The variables outlined below were derived from the 2025 Artificial Intelligence Index report, produced by the Institute for Human-Centered AI at Stanford University. First published in 2017, this annual report aims to monitor the global development of artificial intelligence, assess its societal, economic, and ethical implications, and promote transparency and accountability within the field. The index is distinguished by its incorporation of open datasets, commitment to independence and transparency, and objective assessment of global competition. In this study, we utilized variables from the economic section of the index. A dataset was constructed using data from 47 countries with complete observations. Due to certain constraints, including the unavailability of data from specific countries, high correlations among selected variables, and the study's objectives, five variables were chosen for analysis.

Relative AI Hiring Year-over-Year Ratio, 2018–2024: This indicator reflects the relative difference between the annual growth rate of AI-related Hiring in a specific country, based on LinkedIn users, and the overall annual change in general Hiring within the same country. It serves as a critical measure for analyzing how dynamics in the AI sector compare to trends in the broader labor market. A value above 1 indicates that AI Hiring is growing faster than general Hiring in the country, whereas a value below 1 suggests that AI Hiring is lagging behind the overall Hiring trend. This variable provides an important comparative metric for assessing the development momentum of the AI sector at the country or regional level and for evaluating the effectiveness of policies, investments, and education strategies. Data were recorded monthly from 2018 to 2024, with annual averages computed for each year and then averaged over the six-year period. This variable is expressed as a percentage.

Relative AI Skill Penetration Rate, 2015–2024: This indicator measures the relative share of AI-related skills among the skills listed in LinkedIn profiles across different occupational groups over time. It allows for a comparative analysis of the concentration of AI skills across professions and, by considering changes over the years, highlights the structural impact of AI technologies on the workforce.

Percentage Change in AI Talent Concentration, 2016–2024: This metric represents the relative change over time in the proportion of individuals identified as possessing AI skills within a country's total LinkedIn user base. It is used to evaluate the growth rate of the AI workforce and to compare the evolution of AI human capital across countries or regions. This indicator facilitates the analysis of the momentum of AI specialization in the labor market.

Net AI Talent Migration per 10,000 LinkedIn Members, 2019–2024: This indicator expresses the net migration of AI talent in a given country between 2019 and 2024, per 10,000 LinkedIn members. It is an important measure for assessing where AI talent is moving or leaving, reflecting a country's attractiveness and its gains or losses in AI capabilities. A positive value indicates that the country is a net attractor of AI talent, while a negative value signals a potential brain drain risk.

Number of Newly Funded AI Companies, 2013–2024: This metric represents the annual number of AI-focused companies in a country that received financing for the first time from venture capital, private equity, or similar sources. It is used to measure the size, regional distribution, and evolution of AI start-ups. This indicator serves as a critical empirical tool for analyzing venture-driven growth dynamics, investment activity, and the geographic distribution of innovative capacity in AI.

Table 1: Importance of Variables

Variable Name	Concept Measured	Significance
Relative AI Hiring Year-over-Year Ratio	Annual change in AI-related Hiring relative to overall Hiring.	Reflects the growth dynamics of the AI sector within the country.
Relative AI Skill Penetration Rate	The prevalence of AI-related skills in LinkedIn profiles relative to other skills.	Indicates the dissemination of AI skills across different occupations.
Percentage Change in AI Talent Concentration	Temporal change in the proportion of AI specialists within the total user base.	Provides information on the growth momentum of the AI workforce.
Net AI Talent Migration per 10,000 Members	Net migration of AI talent.	Measures the attractiveness of a country for AI talent.
Number of Newly Funded AI Companies	Number of AI-focused start-ups receiving funding for the first time.	Serves as an indicator of entrepreneurial activity and innovation potential.

3.3. K-Means

K-means is a fundamental iterative algorithm in the field of numerical unsupervised learning, providing a straightforward and intuitive approach to addressing classical clustering problems. This method operates iteratively, striving to identify progressively improved solutions at each step, with the goal of achieving a locally optimal outcome. Each resulting cluster operates independently of the others and maintains internal consistency. In this context, clusters exhibit homogeneity within themselves while demonstrating heterogeneity across different clusters. As a result, K-means has proven to be valuable not only in classification, data mining, and machine learning but also for researchers in applied disciplines such as marketing research, bioinformatics, customer relationship management, engineering, and related fields (Kodinariya & Makwana, 2013; Na et al., 2010).

Originally developed by MacQueen in 1967, the algorithm is outlined as follows (Kodinariya & Makwana, 2013).

$$\boldsymbol{Objective\ Function}: \quad W(S,C) = \sum_{k=1}^{K} \sum_{i \in S_k} \|y_i - c_k\|^2$$

Here, a set of entities represented by vectors $y_{(i)}(i \in I)$ in an S, M dimensional feature space is partitioned into K clusters, each consisting of non-empty, non-overlapping subsets S_k with a corresponding cluster center $c_k(k = 1,2, \dots K)$ The objective of the algorithm is to minimize the squared error function in its objective function. Through this structure, the K-means algorithm organizes all data points into well-defined, distinct groups clustered around respective centroids. The goal is to minimize the distance between each data point and the centroid of its assigned cluster, which is achieved by reducing the total within-cluster variance.

The algorithm proceeds as follows:

Initialization: Place K initial points in the feature space, representing the initial cluster centroids.

Assignment: Assign each data point to the nearest cluster centroid.

Update: After all points are assigned, recompute the centroid of each cluster.

Iteration: Repeat steps 2 and 3 until the cluster centroids remain fixed (i.e., their positions no longer change).

3.4. Determination of the Number of Clusters

3.4.1. By rule of Thumb

This method represents one of the simplest approaches for determining the number of clusters. It serves as a practical technique applicable to various dataset types, allowing for quick estimation without complex computations. However, its accuracy is limited compared to more advanced methods (Kodinariya & Makwana, 2013).

3.4.2. Elbow Method

The Elbow method, one of the earliest techniques, employs a visual approach utilizing explained variance to identify the true number of clusters within a dataset (Bholowalia & Kumar, 2014). Clustering begins with K = 2, and the number of clusters is incrementally increased, performing clustering for each K value. The total within-cluster error is calculated at each step. Initially, a significant reduction in error is observed; however, after a certain K, the rate of decrease diminishes, forming a curve resembling an “elbow.” This “elbow point” indicates the optimal number of clusters.

3.4.3. Information Criterion Approach

Model selection techniques based on mixture models are utilized to ascertain the optimal number of clusters (Bozdogan, 1994). This approach considers the monotonic increase in model dimension and likelihood as the number of clusters in a mixture model rises. In maximum likelihood-based models, information criteria (such as AIC and BIC) penalize the number of parameters to reduce the risk of overfitting, thereby assisting in identifying the optimal cluster count.

3.4.4. Information Theory-Based Approach

Based in rate distortion perception (RDP) theory, this method evaluates within-cluster dispersion through the concept of “distortion” while imposing minimal parametric assumptions. The jump statistic proposed by Sugar and James provides a mathematically supported and effective technique for determining the number of clusters in Gaussian mixture models (Sugar & James, 2003).

3.4.5. Silhouette Method

The silhouette method employs indices that compare intra cluster compactness with inter-cluster separation (Milligan & Cooper, 1985). It determines the optimal K based on the average distance width (Thilagamani & Shanthi, 2010). By assessing the difference between the average distance of each data point to its assigned cluster and other clusters, this method quantitatively evaluates clustering quality. The highest average silhouette value signifies the ideal number of clusters.

3.4.6. Cross-Validation

Proposed by Smyth, the cross-validation method emphasizes cluster stability (Smyth, 1996). The dataset is partitioned into various subsets, with one subset used for clustering and another for model validation. A robust algorithm is expected to produce consistent and reproducible clusters when applied to data drawn from the same source.

3.4.7. Gap Statistic Method

The Gap statistic quantifies the difference in total within-cluster heterogeneity between the observed dataset and reference datasets generated through random sampling (Tibshirani et al., 2001). While both the Gap and Silhouette methods provide a numerical foundation for determining the number of clusters, the Elbow method relies more heavily on the researcher’s judgment. These methods can be employed in conjunction with or as alternatives to criteria such as BIC or AIC.

4. Results

Before conducting the clustering analysis, a correlation analysis was performed to examine the relationships among the variables. Correlation analysis determines the strength of associations between variables. High correlation between two or more variables may result in redundant information, potentially leading to misleading analytical outcomes. In other words, correlation analysis identifies which variables are interdependent and which are independent. Therefore, performing correlation analysis prior to clustering enhances the formation of meaningful clusters.

The results of the Pearson correlation analysis indicate that the variables selected for clustering generally exhibit low levels of linear association ($r < 0.8$), suggesting that they represent distinct dimensions within the data space and can contribute uniquely to the clustering structure. However, the moderate positive correlation observed between Skill Penetration and Funded AI Companies ($r = 0.64$) indicates that these two variables may share partially overlapping information and could influence clustering in a similar direction. Furthermore, the correlations of Talent Migration with all other variables were found to be very low, indicating that it represents an independent and distinctive dimension in the dataset, potentially enhancing heterogeneity in the clustering results. Overall, the dataset does not present a high risk of multicollinearity, providing a suitable multidimensional structure for clustering analysis.

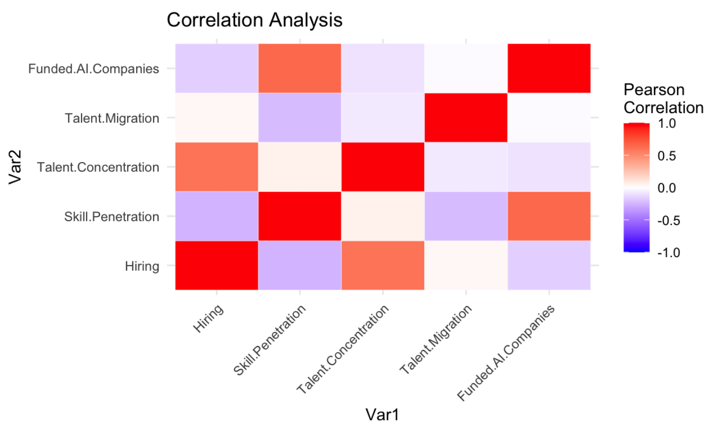

Fig 1: Correlation Analysis

Utilizing box plots, five distinct artificial intelligence (AI) indicators were analyzed, revealing both similarities and differences in distributions across various countries. The first indicator, Hiring, reflects the annual change in AI hiring rates within countries. Saudi Arabia (SAU), Cyprus (CYP), and Uruguay (URY) emerge as outliers, positioned above the median value. The second indicator, Skill Penetration, highlights the United States (USA) and India (IND) as significant outliers with high penetration rates, indicating a substantial concentration of qualified AI workforce in these nations. In contrast, values for other countries in this variable are closer to the median, resulting in a positively skewed distribution characterized by right-skewness. The third indicator, Talent Concentration, measures the change in AI talent concentration across countries. Although no distinct outliers are identified for this indicator, the wide interquartile range suggests varied levels of change in AI talent concentration among countries. The fourth indicator, Talent Migration, reflects the net migration rate of AI specialists. Luxembourg (LUX), Cyprus (CYP), Switzerland (CHE), and Estonia (EST) are recognized as notable outliers for this measure. The distribution is highly skewed, with most countries near the median exhibiting low migration rates. Lastly, the Newly Funded AI Companies indicator quantifies the number of newly established AI companies that have secured investment. The United States (USA) is a prominent outlier, establishing itself as the global leader in AI entrepreneurship. Additionally, countries such as the United Kingdom (GBR), Israel (ISR), Canada (CAN), France (FRA), and India (IND) form a secondary group that attracts moderate levels of investment. The distribution for this indicator is highly skewed; while many countries report very low values, only a select few achieve significant investment levels.

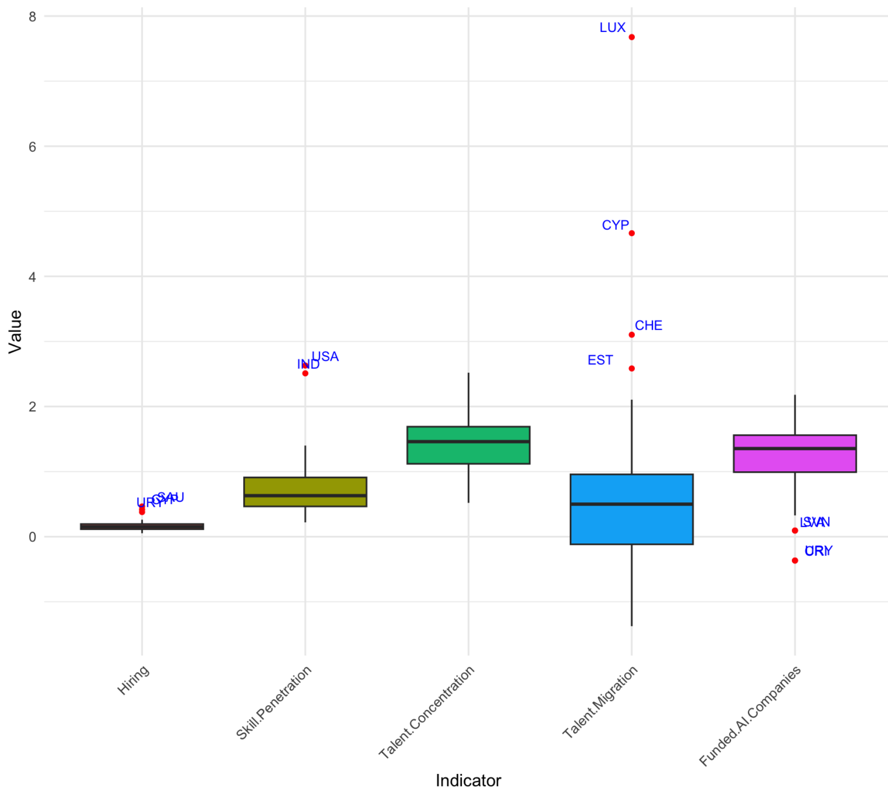

Fig 2: Boxplots of 5 AI Indicators with Outlier Country Labels

The Winsorization method is a statistical adjustment technique utilized to mitigate the influence of outliers on analysis outcomes. It offers several advantages, including resistance to outliers, preservation of the original data's order and arrangement, and simplicity. However, it also presents certain drawbacks: the subjectivity involved in modifying extreme values, potential changes to the distribution and shape of the data, and the risk that results may be affected by the selection of the threshold value (Barnett et al., 1994). The 2.5% Winsorization method is particularly suitable for datasets that approximate a normal distribution yet contain a limited number of outliers. This approach minimizes the disruptive effects of extreme values on modeling while maintaining fidelity to the original characteristics of the data. Consequently, it enhances the statistical robustness of analyses, ensuring that results remain resilient to deviations caused by outliers. An examination of the box-plot graph indicates the presence of outliers within the variables. As such, observations within the lowest 2.5% and highest 2.5% of the dataset were capped at the 2.5th and 97.5th percentile values, respectively, preventing extreme low or high observations from exceeding these pre-established thresholds.

Subsequent to the correlation analysis, a clustering analysis was conducted to categorize countries with similar characteristics. The elbow method was employed to ascertain the optimal number of clusters. The distinctive feature of the Elbow method lies in its reliance on a visual and heuristic assessment rather than a strictly statistical criterion. The method examines the reduction in the within-cluster sum of squares (WCSS) as the number of clusters increases, with the goal of identifying the point at which the marginal gain in explanatory power diminishes significantly. This inflection point, referred to as the "elbow," is interpreted as the optimal number of clusters. In contrast to approaches such as information criteria (AIC, BIC), the Silhouette index, or the Gap statistic which provide a numerical or probabilistic framework for decision-making the Elbow method requires the researcher to visually interpret the curve. While this makes it intuitive, computationally simple, and broadly applicable, it also introduces a degree of subjectivity, potentially reducing its precision relative to more formalized methods. According to this method, the analysis indicated that the ideal number of clusters for the dataset was three. However, as illustrated in Figure 2, an examination of the Total Within Sum of Squares (WSS) values corresponding to the number of clusters reveals a distinct inflection point (elbow) at k=4. Up to this point, the WSS value decreases rapidly; beyond four clusters, the rate of decrease levels off as the number of clusters increases. This suggests that four clusters adequately capture the underlying structure of the dataset, and increasing the number of clusters beyond this threshold would not yield significant contributions to the model. Therefore, the optimal number of clusters was established as four.

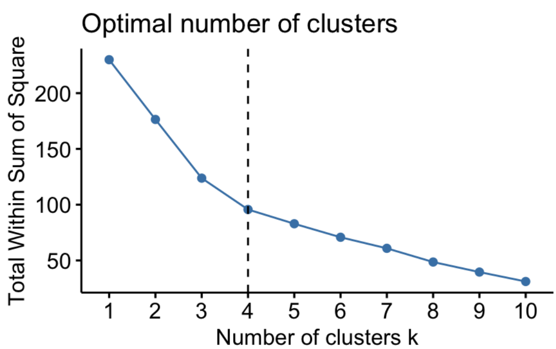

Fig 3. Optimal Number of Clusters

Clusters

The two-dimensional visualization derived from Principal Component Analysis (PCA) effectively summarizes the data structure. The first and second principal components account for 46.1% and 24.8% of the variance, respectively, providing a cumulative information content of 70.9%. This facilitates a clear visual assessment of the cluster structure. The countries assigned to the four clusters identified by the K-Means algorithm are distinctly separated within the two-dimensional plane. These findings indicate that the PCA + K-Means methodology successfully captures the structural distinctions present in the dataset.

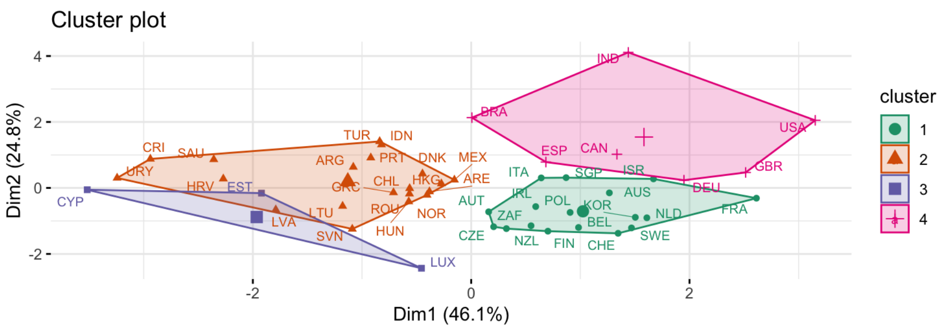

Fig 4. Cluster Plot

Cluster 1 demonstrates significant levels in Talent Migration (0.73) and Newly Funded AI Companies (4.54), while showing the lowest values in Hiring (0.11) and Talent Concentration (1.04). Cluster 2 reveals elevated levels in Hiring (0.21) and Talent Concentration (1.70), alongside a low value in Skill Penetration (0.55), and the lowest levels in Talent Migration (0.18) and Newly Funded AI Companies (2.52). Cluster 3 records the highest values in Hiring (0.27), Talent Concentration (1.80), and Talent Migration (4.97), while showing the lowest level in Skill Penetration (0.26) and a low value in Newly Funded AI Companies (2.62). Cluster 4 exhibits the highest levels in Skill Penetration (1.65) and Newly Funded AI Companies (6.15), while Hiring (0.14), Talent Concentration (1.67), and Talent Migration (0.57) remain at low levels.

Table 3: K-Means Result

Clusters	Hiring	Skill Penetration	Talent Concentration	Talent Migration	Funded AI Companies
Cluster 1, Mean	0.11 (Lowest)	0.73 (High)	1.04 (Lowest)	0.73 (High)	4.54 (High)
Countries, n=17	AUS, AUT, BEL, CHE, CZE, FIN, FRA, IRL, ISR, ITA, KOR, NLD, NZL, POL, SGP, SWE, ZAF				
Cluster 2, Mean	0.21 (High)	0.55 (Low)	1.70 (High)	0.18 (Lowest)	2.52 (Lowest)
Countries, n=20	ARE, ARG, CHL, CRI, DNK, GRC, HKG, HRV, HUN, IDN, LTU, LVA, MEX, NOR, PRT, ROU, SAU, SVN, TUR, URY				
Cluster 3, Mean	0.27 (Highest)	0.26 (Lowest)	1.80 (Highest)	4.97 (Highest)	2.62 (Low)
Countries, n=3	CYP, EST, LUX				
Cluster 4, Mean	0.14 (Low)	1.65 (Highest)	1.67 (Low)	0.57 (Low)	6.15 (Highest)
Countries, n=7	BRA, CAN, DEU, ESP, GBR, IND, USA				

Upon reviewing the clustering results, certain variables demonstrate both positive and inverse trends across the clusters. Notably, Skill Penetration and Talent Concentration exhibit inverse relationships in all four clusters. Clusters characterized by high (Cluster 1) or the highest (Cluster 4) average Skill Penetration show very low (Cluster 1) and low (Cluster 4) averages in Talent Concentration, a pattern that is also evident in Clusters 3 and 4. In contrast, clusters with low (Cluster 2) or very low (Cluster 3) averages of Skill Penetration correspond to high (Cluster 2) and very high (Cluster 3) averages in Talent Concentration.

A positive directional pattern is observed between Skill Penetration and the number of Funded AI Companies across the clusters. Cluster 4, which has the highest average Skill Penetration, also demonstrates the highest average number of Funded AI Companies. Similarly, Cluster 1, characterized by a high average Skill Penetration, exhibits a correspondingly high average in Funded AI Companies. In contrast, Cluster 2, with a low average Skill Penetration, is associated with a significantly lower average in Funded AI Companies, while Cluster 3, which has the lowest average Skill Penetration, reflects a similarly low average in Funded AI Companies.

The first cluster consists of countries distinguished by high Skill Penetration (0.73) and a notable number of Funded AI Companies (4.54), reflecting a strong integration of AI technologies into the workforce. While the hiring rate in these countries is the lowest among all clusters (0.11), this indicates that the existing workforce is largely equipped with AI competencies. As a result, the demand for AI-related human resources is addressed not through new hiring but through skill transformation among current employees. Additionally, this cluster exhibits the lowest average Talent Concentration (1.04) across all clusters, suggesting that AI expertise is more evenly distributed throughout the workforce rather than concentrated among a select few individuals. Moreover, the high capacity to attract international AI specialists (Talent Migration: 0.73) indicates that these countries serve as appealing hubs for technical expertise. In this context, the first cluster represents a framework where AI is deeply integrated into productive sectors, skill transformation is actively pursued, and the investment climate is well-established.

While the countries in the first cluster have generally achieved a degree of maturity in integrating AI technologies into their workforce systems, as evidenced by a high number of funded AI companies, they display significant divergences across specific indicators. In this context, analyzing countries that excel in each key variable is essential for formulating targeted, country-specific policy recommendations. For instance, France demonstrates the lowest hiring rate (0.05) alongside the highest skill penetration (1.23), suggesting that the demand for AI-related recruitment has nearly diminished while the existing workforce possesses strong digital competencies. However, its talent concentration (0.52) is also the lowest, indicating that AI expertise is broadly distributed rather than concentrated within specific groups. Consequently, a recommended policy for France would involve shifting from merely disseminating digital skills to strategically channeling these competencies into key vertical sectors and directing them toward initiatives focused on the development of domestic AI solutions. Conversely, Italy exhibits the highest Hiring value within the cluster (0.15) but falls below average in other indicators, such as skill penetration and talent migration. This implies that while the quantity of AI human capital is increasing, qualitative transformation has not yet been fully realized. Therefore, Italy's policy focus should prioritize enhancing the skill profiles of newly hired personnel and expanding sector-wide reskilling programs. For New Zealand, which displays the weakest skill penetration within the cluster (0.39), targeted education policies should be developed for priority sectors, addressing the skill gap in close alignment with labor market needs.

The countries in the second cluster have made notable progress in AI development, particularly in employment and talent concentration. However, they demonstrate a limited framework concerning skill penetration, international talent attraction, and entrepreneurial capacity. The cluster averages indicate a relatively high hiring variable (0.21), suggesting that these countries are actively implementing recruitment strategies to enhance their AI human capital. Despite this increase in employment, there has yet to be a transformative dissemination of skills across the workforce, as evidenced by a Skill Penetration average of only 0.55. This figure indicates that AI competencies are not adequately integrated across various sectors. Furthermore, the Talent Concentration variable is relatively high at 1.70, suggesting that expertise is concentrated within specific institutions. The lowest cluster average is found in the Talent Migration indicator (0.18), which underscores the challenges these countries face in attracting international AI talent and their potential vulnerability to brain drain. Lastly, the average number of funded AI companies is only 2.52, reflecting limited entrepreneurial capacity and modest levels of investment in AI.

The third cluster, comprising Cyprus, Estonia, and Luxembourg, presents the most distinctive profile among all clusters. This cluster demonstrates the highest average Hiring rate (0.27) and the highest Talent Migration rate (4.97), while concurrently exhibiting the lowest Skill Penetration (0.26). This pattern indicates that, despite a strong attraction of foreign AI expertise to these countries, there are considerable challenges in transferring these skills to the local workforce.

The fourth cluster consists of countries exhibiting the highest values in Skill Penetration and Funded AI Companies. The cluster's average Skill Penetration score of 1.65 signifies the most advanced level, indicating that AI related skills are widely distributed throughout the workforce rather than limited to a select group of specialists. Furthermore, the average score of 6.15 for Funded AI Companies ranks highest among the clusters, suggesting not only robust capacity development but also the successful conversion of this capacity into tangible products and services, indicative of effective commercialization. In contrast, the indicators for Hiring (0.14), Talent Migration (0.57), and Talent Concentration (1.67) demonstrate relatively moderate levels. This configuration suggests that AI development in these countries is more established and sustained by internal dynamics.

A one-way analysis of variance (ANOVA) was performed to assess significant differences among the clustered countries concerning the five core artificial intelligence indicators. The results reveal that inter-cluster differences are statistically significant across all variables ($p < 0.05$). This finding indicates that both AI hiring trends in the labor market and AI-related entrepreneurial activities exhibit heterogeneous structures across the clusters. These results imply that the clusters represent not just superficial groupings but rather reflect substantive structural differences in terms of AI capacity, human capital dynamics, and innovative entrepreneurial potential.

Table 4: Anova Results

Variables	F	p	Significant (p<0.05)
Hiring	10.87	0.00	Yes
Skill Penetration	24.96	0.00	Yes
Talent Concentration	12.34	0.00	Yes
Talent Migration	22.23	0.00	Yes
Funded AI Companies	23.70	0.00	Yes

5. Discussion

The inverse relationship observed between Skill Penetration and Talent Concentration indicates a structural dynamic emphasized by researchers such as Leoste et al. (2021), B. D. Lund & Wang (2023), and Bejaković & Mrnjavac (2020). These studies emphasize that the widespread dissemination of AI skills across the workforce is achievable not only through individual effort but also via institutional and societal learning mechanisms. As observed in the first cluster, high skill penetration alongside low Talent Concentration indicates that competencies are not confined to narrow expert groups but are distributed more horizontally and inclusively. This finding validates the skill distribution model evident in societies where AI technologies are adopted in a more democratic and pervasive manner (Choi, 2021; Jiao et al., 2023). Additionally, the inverse pattern observed between Skill Penetration and Talent Concentration points to a structural issue highlighted by researchers such as Leoste et al. (2021), B. D. Lund & Wang (2023), and Bejaković & Mrnjavac (2020). These studies emphasize that the widespread dissemination of AI skills across the workforce is achievable not only through individual effort but also via institutional and societal learning mechanisms. As observed in the first cluster, high skill penetration alongside low Talent Concentration indicates that competencies are not confined to narrow expert groups but are distributed more horizontally and inclusively. This finding validates the skill distribution model evident in societies where AI technologies are adopted in a more democratic and pervasive manner (Choi, 2021; Jiao et al., 2023).

Furthermore, the observed inverse relationship between Skill Penetration and Talent Concentration highlights a structural issue identified by researchers such as Leoste et al. (2021), Lund & Wang (2023), and Bejaković & Mrnjavac (2020). These studies contend that the dissemination of AI skills across a diverse workforce is supported not only by individual efforts but also through institutional and societal learning mechanisms. As noted in the first cluster, high skill penetration coupled with low talent concentration suggests that competencies are distributed horizontally and inclusively, rather than being limited to narrow expert groups. This finding reinforces the model of skill distribution observed in societal structures where AI technologies are adopted more democratically and broadly (Choi, 2021; Jiao et al., 2023).

The notably high average of Talent Migration in the third cluster indicates that these countries are effective in attracting foreign sourced AI specialists. However, the critical question is whether this migration translates into local capacity. Mannuru et al. (2023) and Schiff (2022) emphasize that, particularly in developing countries, AI talent migration carries the risk of exacerbating structural weaknesses, and without the establishment of local innovation systems, such inflows may fail to generate lasting benefits. From this perspective, the combination of high Talent Migration levels and low Skill Penetration in countries like Luxembourg, Estonia, and Cyprus reflects the "cognitive transfer gap" highlighted by Schiff. Although these countries benefit from external expertise, the acquired knowledge is insufficiently diffused within the local workforce, preventing the formation of a sustainable knowledge based economy.

High values in the Hiring indicator observed in the second and third clusters suggest that countries are actively seeking to quantitatively expand their AI workforce. However, without adequate support for skill transformation and entrepreneurial initiatives, these efforts do not result in structural development. White et al. (2023) and Islam et al. (2024) contend that AI-based employment strategies should be evaluated not only by the quantity of hires but also by the quality of employment and its integration into organizational processes. Notably, even in countries with high Hiring levels, the persistently low values of Skill Penetration and Funded AI Companies highlight this strategic misalignment.

Furthermore, the findings align with comparative analyses of AI strategies conducted by Al-Marzouqi & Arabi (2024) and Wang et al. (2025). These studies underscore that the advancement of AI should be assessed not solely in terms of investment and technical capacity but also through human capital development, policy orientation, and cultural frameworks. Specifically, differences in AI policy priorities between the EU and the U.S. (Djeffal et al., 2022; Guenduez & Mettler, 2023) suggest that cluster distinctions among countries reflect not only technical capacities but also structural and contextual divergences.

5.1. Practical İmplications and Policy Recommendations

In the first cluster, Singapore distinguishes itself with the highest Talent Concentration (1.57), indicating a structure where AI experts are centralized within limited groups. This highlights the necessity of implementing mechanisms that encourage increased talent rotation and horizontal mobility between the public and private sectors. In contrast, Israel has the lowest Talent Migration value within the cluster (-0.23) while leading in the number of Funded AI Companies (492). This notable trend suggests that, despite possessing a robust domestic investment capacity, the influx of foreign expertise remains constrained. Therefore, recommended strategies for Israel should include the promotion of international fellowship programs and academic mobility initiatives to enhance the attraction of external talent. Switzerland presents a contrasting scenario, leading the cluster in Talent Migration (3.10) but exhibiting relatively low Hiring (0.09) and average Skill Penetration. This indicates a significant opportunity to better leverage international expertise. For Switzerland, prioritizing mentorship and institutional knowledge-transfer programs that enable incoming experts to share their insights with local talent would be strategically beneficial. Finally, South Africa shows the weakest performance within the cluster across Skill Penetration (0.62), Talent Migration (-0.23), and Funded AI Companies (20). This profile suggests that the country is still in the early stages of AI-driven transformation. Consequently, priority objectives should focus on foundational digital skill development, addressing infrastructure disparities, and building capacity through regional collaborations.

One of the notable countries in the second cluster is Saudi Arabia. Despite a relatively high hiring rate of 0.46, the number of funded AI companies remains limited at 13, indicating that recruitment has not effectively translated into skill development. Similarly, Uruguay and Costa Rica exhibit high employment rates but very low skill penetration, suggesting that post hiring training and skill enhancement should be prioritized in these countries. Portugal and Costa Rica stand out with the highest talent concentration values of 2.37 and 2.40, respectively, implying that expertise is concentrated within narrow groups and lacks broader societal diffusion. In countries such as Latvia, skill penetration is extremely low at 0.22, increasing the risk of digital exclusion. In terms of migration, the UAE demonstrates a positive deviation of 2.01; however, effective talent transfer systems are needed to leverage this potential across the workforce. Conversely, Argentina, Greece, and Turkey exhibit negative talent migration, highlighting the necessity for incentives and career opportunities to retain skilled personnel domestically. Finally, in terms of entrepreneurship, only Hong Kong, with a score of 70, significantly exceeds the cluster average. Overall, Funded AI Companies levels in the remaining countries within this cluster are weak, underscoring the importance of promoting public funding initiatives and encouraging private-sector investments.

In the third cluster, Luxembourg demonstrates an exceptionally high Talent Migration value of 7.68; however, its Skill Penetration remains only 0.24. Likewise, Cyprus and Estonia exhibit elevated hiring rates and Talent Migration, yet their skill levels are comparatively low. This trend indicates that AI-related knowledge and practices are confined to narrow circles and have not been widely disseminated throughout the workforce. Furthermore, the Talent Concentration values (CYP: 2.19; EST: 2.07) reinforce this observation. Additionally, the number of funded AI companies in these countries is relatively limited (CYP: 8; EST: 19; LUX: 17). Collectively, these findings suggest that the primary policy recommendation for countries within this cluster should prioritize the development of education-based programs, collaborative project models, and professional frameworks that enable the transfer of externally acquired expertise to domestic resources. By implementing such strategies, these countries can not only attract external talent but also convert it into sustainable local development.

Certain countries within the fourth cluster exhibit distinct characteristics. Germany, despite its relatively low Hiring (0.09) and Talent Concentration (1.40) levels, demonstrates high Skill Penetration (1.32) and significant Talent Migration (2.11). This indicates that while employment growth may be limited, knowledge transformation is robust, and external expertise is effectively integrated. Similarly, Canada surpasses the cluster average with a strong migration capacity (1.47) and a substantial number of Funded AI Companies (481). In contrast, India displays very high Skill Penetration and Talent Concentration but reports a negative Talent Migration value (–1.38). This suggests that domestically trained AI professionals are relocating abroad, posing a potential risk of knowledge loss. To mitigate this issue, policy measures in India could focus on retaining experts by offering competitive career opportunities, establishing national innovation funds, and promoting high-tech-centered business models.

5.2. Future Research

Based on the findings of this study, two recommendations for future research are proposed. First, the discrepancy between AI skill penetration and hiring rates warrants further examination to understand how AI policies in specific countries translate into sectoral outcomes. Investigating this issue extends beyond merely identifying quantitative disparities; it requires an analysis of the political and strategic contexts underlying these differences. Such an approach could elucidate paradoxical cases, such as the third cluster, where high hiring rates coincide with low skill penetration. Second, the systematic divergence of clusters composed of small-scale countries such as the third cluster regarding talent concentration and talent migration merits additional exploration. This inquiry challenges conventional models that focus on large economies and facilitates the identification of structural advantages in smaller, high-performing countries. Furthermore, drawing generalizations from a cluster comprising only a few countries raises important methodological considerations that should be addressed in future studies.

6. Conclusion

The distribution of AI indicators across countries exhibits considerable heterogeneity. While some nations excel in nearly all indicators, others show balanced progress or stand out only in specific metrics. The presence of outliers underscores the growing inequalities in global AI development and highlights the systemic advantages that certain nations. These disparities enable the identification of meaningful groupings through statistical techniques such as cluster analysis. The prevalence of outliers indicates an asymmetric global AI landscape, wherein specific countries obtain systematic advantages, thereby emphasizing the importance of utilizing multivariate statistical methods, such as clustering, to analyze country groupings effectively.

The analysis results indicate that, based on five key AI indicators, countries are categorized into four distinct clusters, each exhibiting significant structural differences in workforce skill integration, international talent attraction, employment strategies, and entrepreneurial capacity. The first cluster consists of countries with a balanced and comprehensive competency profile, which are transforming their existing workforce through reskilling, despite low hiring rates, while demonstrating high skill penetration and investment capacity. The second cluster reveals developmental imbalances, characterized by high employment and talent concentration but limited skill penetration, weak international talent attraction, and low entrepreneurial capacity. The third cluster demonstrates exceptional performance in employment and international talent attraction but faces considerable challenges in transferring these competencies to the local skill base. The fourth cluster includes countries with the highest skill penetration and entrepreneurial capacity, leveraging these advantages through well-established, balanced, and internally driven AI development. These findings suggest that countries' AI strategies should extend beyond merely increasing human capital quantitatively, emphasizing the enhancement of a qualified skill base, improving international talent attraction, and directing investments toward scalable and innovative sectors through comprehensive policy measures.

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