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Classification of Human Resources Readiness in Asia: K-Means Clustering Using R Studio

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Abstract

This research aims to classify dichotomously the differences and diversity in human resources of all countries in the Asian region to clarify the position of each country based on the state of its human resources. Several countries were not included in the analysis due to limited data availability. This research uses the K-Mean clustering method. Clustering is an approach to dividing a set of points into similar groups called clusters. K-Mean clustering is one of the most popular unsupervised learning methods in machine learning. Based on the results of the K-Mean clustering analysis, the readiness of human resources in Asian countries shows that there are clusters or groups, with cluster 1 having as many as 29 members and cluster 2 having as many as 9 members. K-Mean clustering for the optimal number of two clusters is dichotomous, so it uses clustering assumptions between country clusters with good and poor human resource readiness.

Keywords: *GCI, HDI, HCI, Human Resources, K-Means Clustering.*

INTRODUCTION

People cannot be the most critical asset, only the right people (Collins, 2001). Superior human resources are the most valuable asset for a nation to face various opportunities and risks that are increasingly changing rapidly and cannot be predicted. Many institutions have developed an instrument model that addresses the level of human resources in a country, including HDI (Human Development Index) developed by UNDP (United Nations Development Program), HCI (Human Capital Index) by World Bank, and GCI (Global Competitiveness Index) by WEF (World Economic Forum). The HDI was first launched in 1990, representing a paradigm shift in development thinking and measurement (Assa, 2021). HDI shifts the focus of development economics from national income accounting to people-centered policies, with measures that can be used to assess a country's economic and social expansion (Hickel, 2020). HDI has become a widely accepted proxy for human development over the past 30 years (Zhang & Zhu, 2022) and an essential criterion for determining national progress that focuses on people and their capabilities (Sadiq et al., 2022).

HDI is a humanistic instrument published by UNDP, with wealth indicators, gross national income per capita, knowledge indicators, and health and life expectancy indicators (Kancherla et al., 2019). The index is used to evaluate several social issues, such as environmental sustainability, security and human rights, and gender equality, and measure the relationship between these elements and human demographic and ecological attributes such as age, water access, access to financial resources, and education (Ladi et al., 2021; Barrios-Garrido et al., 2020). HDI develops over time, with changes in calculation techniques and dimensional indicators (Abdullahi, 2024; Biggeri & Mauro, 2018; Mangaraj & Aparajita, 2020). HDI identifies criteria for healthy living (Martínez-Mesa et al., 2017; Veisani et al., 2018) and a decent standard of living, which is closely related to quality of life (Martínez-Guido et al., 2019). So, countries with low HDI show low health quality (Hwang et al., 2019), high mortality rates (Pervaiz & Faisal, 2017), and educational inequality (Sarkodie & Adams, 2020). HDI even has a significant influence on the socio-economic (Iskandar et al., 2020; Resce, 2021),

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political harmony of a region (Niranjan, 2020), and the ecological condition of an area (Wang, Danish, Zhang, & Wang, 2018; Long et al., 2020). HDI contributed significantly in emphasizing that economic growth, people, and capabilities should be considered to assess a country's development (Resce, 2021). Apart from HDI, a relevant indicator used as a reference for human resource readiness is HCI (Human Capital Index).

The World Bank Human Capital Index (HCI) aims to provide new information on the future productivity of each country's workforce by synchronizing the available International Large-Scale Assessment (ILSA) and the results of regional test programs (Liu & Steiner-Khamsi, 2020). Countries with high human capital and knowledge indices will more successfully attract efficiency-seeking types of FDI (Foreign Direct Investment) (Sadeghi et al., 2020). HC is a variable in the production function and a direct determinant of economic prosperity (Yu & Deng, 2021). HC (Human Capital) refers to population attributes that, together with physical capital such as facilities, infrastructure, and other tangible assets, contribute to economic productivity (Lim et al., 2018). HC is characterized as the aggregate level of education, training, skills, and health in a population (Campbell & Üngör, 2020); it influences the degree to which technology can be developed, adopted, and used to increase productivity.

HC is considered an important component for the development of economic growth throughout the world (Çakar et al., 2021). HC increases labor productivity, promotes democracy and quality of governance, and increases equality (Aljarallah, 2020). HC is a production factor and has a dual role in improving skills through learning and creating new ideas through R&D (Sankaran, Kumar, & Das, 2020). HC is an integral part of the success or failure of industrial institutional design (Prego, 2021). HC influences innovation strategy and performance (AlQershi et al., 2021), children's welfare (W. Zhang, 2021), corporate financial management (Liu, Liu, & Zhang, 2021), plays a vital role in promoting income equality (Managi et al., 2021), economic growth (Zhang & Wang, 2021; Song, Wei, Zhu, Liu, & Zhang, 2021; Xu & Li, 2020), health (Fink, Venkataramani, & Zanolini, 2021; Wulczyn, Parolini, & Huhr, 2021) and even reciprocally on the ecological condition of an area (Sarkodie, Adams, Owusu, Leirvik, & Ozturk, 2020; Chen, Song, & Wu, 2021; Haini, 2021; Alvarado et al., 2021). Several things that influence HC accumulation include economic growth (Rahim et al., 2021)(Égert et al., 2020), social mobility (Laajaj et al., 2022)(Varghese et al., 2021), demographic changes (Bairoliya & Miller, 2021), energy availability (Rafi et al., 2021) and learning opportunities (Trude et al., 2021). Apart from HCI, GCI (Global Competitiveness Index) or global competitiveness is a possible indicator of a country's human resources readiness.

The Global Competitiveness Index (GCI), elaborated by the World Economic Forum (WEF), is widely applied to evaluate and rank countries depending on the level of global competitiveness (Auzina-Emsina, 2014). The WEF report was published by a leading academic press (Oxford University Press) and masterminded by leading Harvard academics Jeffrey Sachs and Michael Porter (Lall, 2001). The GCI assesses the primary factors and institutions that determine improvements in countries' long-term growth and competitiveness (Önsel Ekici et al., 2019). The elements indicating global competitiveness are categorized into four sub-indices: fundamental provisions, human capital, supporting environment, innovation ecosystem, and market considerations (Auzina-Emsina, 2014). This research assumes synthetically based on available research regarding 3 factors (HDI, HCI, and GCI) as benchmarks for the readiness of a country's human resources. All data related to HDI, HCI, and GCI can be accessed openly, freely, and legally on the Internet (UNDP, 2020; Worldbank, 2021).

RESEARCH METHODS

This research uses the K-Mean clustering method using the r program, K-Mean clustering is one of the most popular unsupervised learning methods in machine learning (Liao et al., 2022), and the classical and effective clustering method (Gu et al., 2021), aims to group or partition data $\{x1, \ldots, xN\}$, $xi \in RM$ into k clusters $\{C1, \ldots, Ck\}$, $k \leq N$ (Hozumi et al., 2021). The goal is to find natural groupings in the data, so that researchers see data groupings as more reasonable (Rencher, 2002). Clustering is an approach to dividing a set of points (data) into similar groups called clusters (Abo-Elnaga & Nasr, 2022). Each cluster is composed of points that are the same and different from other cluster points. Clustering is a very important tool to assist researchers in solving various problems in several fields.

K-Means clustering analysis was explored to identify spatial clustering (Xie et al., 2019). K-Means clustering as a tool for data dimension reduction and multivariate grouping, grouping samples to minimize variation within groups and maximize variation between groups (Kazapoe et al., 2021). Applying the k-means procedure, several indices can be used, including Silhouette, Calinski, Davies, and Dunn (Cerqueti & Ficcadenti, 2022). The K-Mean clustering procedure describes an algorithm that assigns each item to the cluster with the closest centroid (mean) (Johnson & Wichern, 1992). K-means clustering starts by selecting k points as k cluster centers or centroids (Shrifan et al., 2021). Then, each point in the dataset is assigned to the nearest centroid (Zhao et al., 2020). The centroid is then updated by minimizing the within-cluster sum of squares (WCSS), which is defined as follows (Patel & Kushwaha, 2020).

RESULTS AND DISCUSSION

Data on the human resource readiness of countries in the ASIA region can be accessed freely and legally at related institutions (UNDP, World Bank, WEF). Some country data is not included due to limited data availability in Table 1.

Table 1. Human Resource Readiness of Asian Countries

COUNTRIES	HDI	HCI	GCI	COUNTRIES	HDI	HCI	GCI
Brunei Darussalam	0.838	0.63	62.8	Sri Lanka	0.782	0.60	57.1
Indonesia	0.718	0.54	64.6	Turkey	0.820	0.65	62.1
Cambodia	0.594	0.49	52.1	Saudi Arabia	0.854	0.58	70.0
Lao_PDR	0.613	0.46	50.1	Yemen	0.470	0.37	35.5
Malaysia	0.810	0.61	74.6	Jordan	0.729	0.55	60.9
Myanmar	0.583	0.48	3.32	Azerbaijan	0.756	0.58	62.7
Philippines	0.718	0.52	61.9	UAE	0.890	0.67	75.0
Singapore	0.938	0.88	84.8	Israel	0.919	0.73	76.7
Thailand	0.777	0.61	68.1	Lebanon	0.744	0.52	56.3
Viet Nam	0.704	0.69	61.5	Oman	0.813	0.61	63.6
China	0.761	0.65	73.9	Kuwait	0.806	0.56	65.1
Japan	0.919	0.80	82.3	Georgia	0.812	0.57	60.6
South Korea	0.916	0.80	79.6	Armenia	0.776	0.58	61.3
Mongolia	0.737	0.61	52.6	Qatar	0.848	0.64	72.9
India	0.645	0.49	61.4	Bahrain	0.852	0.65	65.4
Pakistan	0.557	0.41	51.4	Cyprus	0.887	0.76	66.6
Bangladesh	0.632	0.46	52.1	Kazakhstan	0.825	0.63	62.9
Iran	0.783	0.59	53.0	Tajikistan	0.668	0.50	52.4
Nepal	0.602	0.50	51.6	Kyrgyzstan	0.697	0.60	54.0

The results of data analysis with K-Mean - Silhouette through the R program consist of descriptive statistics, distance matrix visualization results, results of determining and visualizing the optimal number of clusters, and clustering results.

Table 2. Descriptive Statistics

Vars		N	Mean	Sd	Median	Trimmed	Mad	Min	Max	Range	Skew	Kurtosis	Se
HDI	1	38	0.76	0.11	0.78	0.76	0.11	0.47	0.94	0.47	-0.48	-0.47	0.02
HCI	2	38	0.59	0.11	0.60	0.59	0.08	0.37	0.88	0.51	0.44	0.17	0.02
GCI	3	38	61.13	14.01	62.00	62.10	11.86	3.32	84.80	81.48	-1.66	5.52	2.27

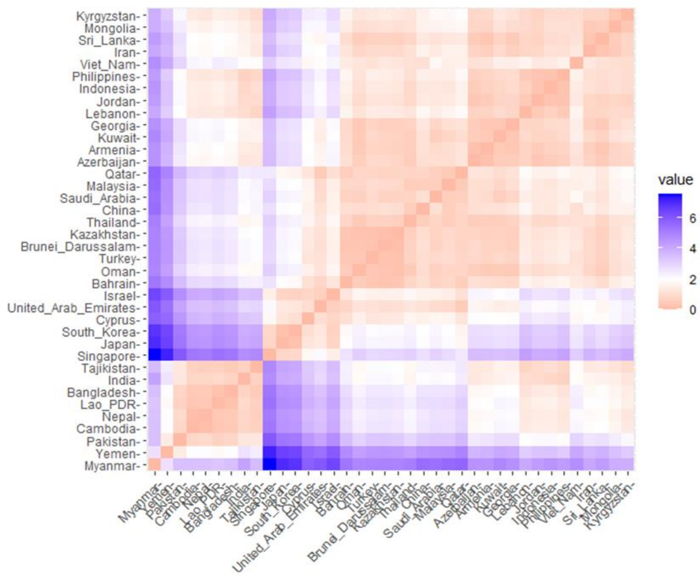

Figure 1. Distance Matrix Visualization

The colors indicate the distance matrix value for each country. K-means clustering is a helpful algorithm for partitioning data into different categories, where the distance between data in the same category must be very close, indicating the most significant similarity between them (Fan et al., 2021). This is intended as a basis for clustering. In the single linkage method, the distance is found for each pair of clusters, and the two clusters with the smallest distance are combined. Therefore, the number of clusters is reduced by 1. Once two clusters are connected, this procedure is repeated for the next step: the distance between all pairs of clusters is calculated again, and the pairs with the minimum distance are combined into one cluster (Rencher, 2002). Meanwhile, this research uses a partition or optimization method, where observations are separated into g clusters without a hierarchical approach based on a distance or similarity matrix between all pairs of points.

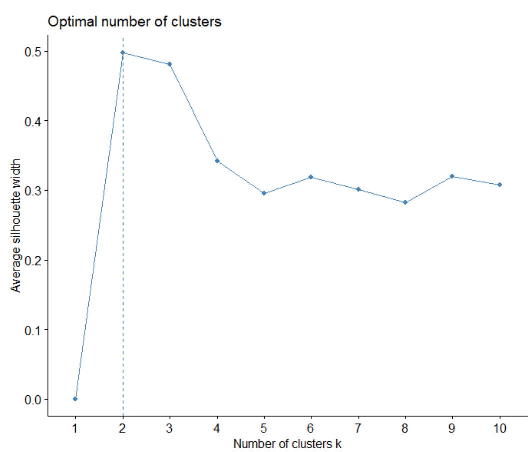

Figure 2. Optimal Number of Clusters

The optimal number of clusters from k-means clustering is determined based on the Bayesian Information Criterion. The clustering results are evaluated using the Silhouette coefficient. Based on the analysis results, it shows that the optimal number of clusters is two clusters. Cluster 2 has the highest Silhouette coefficient, amounting to 0.497. So, it determines the number of clusters.

Table 3. Calculation Results of the Optimal Number of Clusters

Cluster	y
1	0.0000000
2	0.4973394
3	0.4811556
4	0.3421049
5	0.2957281
6	0.3190322
7	0.3010123
8	0.2824029
9	0.3200697
10	0.3070732

Table 4. Clustering Results

Countries	HDI	HCI	GCI	HDI_1	HCI_2	GCI_3	Cluster
Brunei	838	63	628	7,11404E+14	3,3315E+14	1,1943E+14	1
Indonesia	718	54	646	-3,51855E+14	-4,98509E+14	2,47915E+13	1
Cambodia	594	49	521	-1,45056E+14	-9,60541E+14	-6,44337E+14	2
Lao PDR	613	46	501	-1,28221E+14	-1,23776E+14	-7,87098E+14	2
Malaysia	81	61	746	4,6331E+14	1,48337E+14	9,61716E+14	1
Myanmar	583	48	332	-1,54802E+14	-1,05295E+14	-4,12626E+14	2
Philippines	718	52	619	-3,51855E+14	-6,83322E+14	5,51881E+14	1
Singapore	938	88	848	1,59745E+14	2,64331E+14	1,68979E+13	1
Thailand	777	61	681	1,70914E+14	1,48337E+14	4,97745E+14	1
Viet Nam	704	69	615	-4,75902E+14	8,87589E+13	2,66361E+13	1
China	761	65	739	2,91463E+14	5,17963E+13	9,1175E+14	1
Japan	919	8	823	1,4291E+14	1,90406E+14	1,51134E+14	1
South Korea	916	8	796	1,40252E+14	1,90406E+14	1,31862E+14	1
Mongolia	737	61	526	-1,83505E+14	1,48337E+14	-6,08647E+14	1
India	645	49	614	-9,98671E+14	-9,60541E+14	1,94981E+14	2
Pakistan	557	41	514	-1,77839E+14	-1,69979E+14	-6,94304E+14	2
Bangladesh	632	46	521	-1,11386E+14	-1,23776E+14	-6,44337E+14	2
Iran	783	59	53	2,24077E+14	-3,64763E+14	-5,80095E+13	1
Nepal	602	5	516	-1,37967E+13	-8,68135E+13	-6,80027E+14	2
Sri Lanka	782	6	571	2,15217E+14	5,59303E+14	-2,87437E+14	1
Turkey	82	65	621	5,51915E+14	5,17963E+13	6,94642E+14	1
Saudi Arabia	854	58	70	8,53172E+14	-1,28883E+14	6,33367E+14	1
Yemen	47	37	355	-2,54926E+14	-2,06942E+13	-1,82925E+14	2
Jordan	729	55	609	-2,54389E+14	-4,06102E+14	-1,6192E+14	1
Azerbaijan	756	58	627	-1,51561E+14	-1,28883E+14	1,12292E+14	1
UAE	89	67	75	1,17215E+14	7,02776E+14	9,90268E+14	1
Israel	919	73	767	1,4291E+14	1,25721E+14	1,11161E+14	1
Lebanon	744	52	563	-1,21482E+14	-6,83322E+14	-3,44541E+14	1
Oman	813	61	636	4,89892E+14	1,48337E+14	1,76534E+14	1
Kuwait	806	56	651	4,27868E+13	-3,13696E+14	2,83605E+14	1
Georgia	812	57	606	4,81031E+14	-2,21289E+14	-3,76061E+14	1
Armenia	776	58	613	1,62054E+14	-1,28883E+14	1,236E+14	1
Qatar	848	64	729	8,00009E+13	4,25556E+14	8,4037E+14	1
Bahrain	852	65	654	8,35451E+14	5,17963E+13	3,05019E+14	1
Cyprus	887	76	666	1,14557E+14	1,53443E+13	3,90675E+14	1
Kazakhstan	825	63	629	5,96218E+14	3,3315E+14	1,26568E+14	1
Tajikistan	668	5	524	-7,94879E+14	-8,68135E+13	-6,22923E+14	2
Kyrgyzstan	697	6	54	-5,37925E+14	5,59303E+14	-5,08715E+14	1
Total	Cluster 1				Cluster 2		
	29				9		

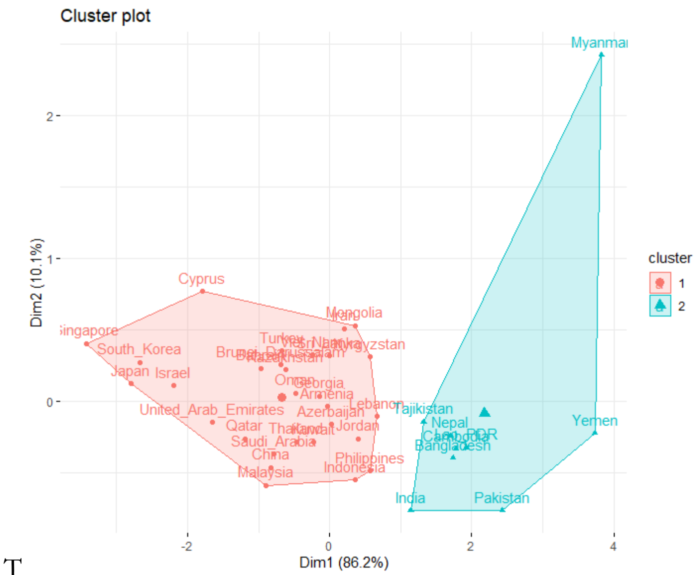

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Figure 3. Cluster Visualization

Based on the results of the K-Mean clustering analysis, the readiness of human resources in Asian countries shows that there are clusters or groups with the number of cluster 1 as many as 29 members and cluster 2 as many as 9 members, each clustered with color indication and dots or points indicating the distance. K-Mean clustering for the optimal number of two clusters is dichotomous, using cluster assumptions between good and poor human resource readiness.

CONCLUSION

Based on the results of the K-Mean clustering analysis, it is concluded that there are two clusters of human resource readiness in the Asian region, as follows: The group or cluster of countries with good human resource readiness consists of Singapore, Japan, South Korea, Cyprus, UAE, Israel, Bahrain, Oman, Turkey, Brunei Darussalam, Kazakhstan, Thailand, China, Saudi Arabia, Malaysia, Qatar, Azerbaijan, Armenia, Kuwait, Georgia, Lebanon, Jordan, Indonesia, Philippines, Viet Nam, Iran, Sri Lanka, Mongolia, Kyrgyzstan. The group or cluster of countries with poor human resource readiness consists of Tajikistan, India, Bangladesh, Lao PDR, Nepal, Cambodia, Pakistan, Yemen, and Myanmar.

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