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MAPPING DIGITAL READINESS TO SUPPORT AN INCLUSIVE DIGITAL ECONOMY USING INDONESIA'S DIGITAL SOCIETY INDEX

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A B S T R A C T

Digital transformation in Indonesia has become a key driver for promoting inclusive economic development by enhancing access, building digital capacities, and empowering communities within the digital economy. Despite national-level efforts, regional disparities in digital readiness remain evident, with some provinces lagging in infrastructure, digital skills, and community empowerment. This study aims to identify regional characteristics based on digital economic inclusivity using K-Means clustering applied to four main dimensions of the Indonesian Digital Society Index (IMDI): digital infrastructure and ecosystems, digital skills, community empowerment, and employment. The analysis identifies three distinct clusters of provinces: Cluster 1 with medium digital readiness, characterized by moderate infrastructure, skills, and empowerment but relatively higher employment; Cluster 2 with low digital readiness across nearly all indicators; and Cluster 3 with high digital readiness, with strong infrastructure, skills, and empowerment, although employment remains moderate. The findings reveal significant regional disparities and provide essential insights for policymakers to design targeted strategies that foster a more inclusive digital economy in Indonesia.

Keywords:
Cluster Analysis, Inclusive Digital Economy, IMDI, Digital Transformation

1. INTRODUCTION

Digital transformation has become one of the main drivers of structural changes in the global economy by enhancing efficiency, productivity, and expanding access to technology-based economic opportunities. From the perspective of the digital economy, Bukht and Heeks (2017) define the digital economy as economic activities mediated by digital technologies in the processes of production, distribution, and consumption. This development creates new opportunities for economic growth, while at the same time posing challenges in the form of unequal use of technology. The benefits of the digital economy are not automatically experienced evenly by all segments of society and may therefore exacerbate social and economic inequalities if not accompanied by policies oriented toward inclusivity (World Bank, 2016; OECD, 2019).

Digital inequality is therefore not limited to disparities in access to technology but also encompasses differences in digital skills and the capacity to effectively use technology (Jayanthi & Dinaseviani, 2022). Consequently, digital transformation initiatives that focus solely on infrastructure provision risk generating digital exclusion when communities lack adequate capacity to utilize digital technologies productively. For this reason, inclusivity constitutes a key element in digital economic development, especially in developing countries with diverse social and geographical characteristics such as Indonesia.

Within the framework of digital development, the concept of digital readiness is essential for explaining the extent to which societies are prepared to engage in digital transformation. The OECD (2019) and the World Bank (2021) emphasize that digital readiness is determined by a combination of digital infrastructure availability, digital skills and literacy, and the capacity to apply digital technologies in economic and social activities. This framework positions human resources as a central factor bridging technological advancement and economic value creation. In line with this perspective, the G20 developed the *G20 Toolkit for Measuring Digital Skills and Digital Literacy* as a global reference for assessing societal readiness for digital transformation, with a focus on digital skills, digital literacy, and

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community empowerment as the foundations of a sustainable and inclusive digital economy (G20, 2018).

In Indonesia, efforts to measure societal digital readiness are manifested through the development of the Indonesian Digital Society Index (Indeks Masyarakat Digital Indonesia/IMDI) by the Ministry of Communication and Digital Affairs of the Republic of Indonesia. IMDI is a composite index developed with reference to the G20 Toolkit and consists of four main dimensions: digital infrastructure and ecosystem, digital skills, digital empowerment, and employment. These dimensions are designed to comprehensively represent societal digital readiness, ranging from the availability of supporting infrastructure and enabling environments, individual capacity to use digital technologies, the ability to utilize technology productively and safely, to the linkage between digital readiness and economic and employment activities (Ministry of Communication and Digital Affairs of the Republic of Indonesia, 2024). The digital skills and employment dimensions of IMDI are consistent with human capital theory as proposed by Becker (1964), which posits that investment in skills enhances productivity and employment opportunities, particularly in technology-based economies.

Nevertheless, digital readiness in Indonesia is not homogeneous. Variations in geographical, social, and economic conditions across regions result in significant disparities in levels of digital readiness. Such inequalities in digital readiness may hinder the realization of an inclusive digital economy, as regions with lower levels of readiness risk being left behind in the digital transformation process and in accessing technology-based economic opportunities (UNDP, 2020). Therefore, mapping digital readiness is a strategic step in identifying patterns and disparities in digital readiness across regions.

Based on this theoretical framework, this study aims to map the level of digital readiness in Indonesia through cluster analysis of the IMDI. This approach is employed to group regions according to their digital readiness characteristics, thereby providing a typology of regions that can serve as an evidence-based foundation for policymaking in support of inclusive digital economic development.

2. METHOD

Data and Data Sources

This study employs a quantitative approach using secondary data from the Indonesian Digital Society Index (IMDI) for 2024, published by the Ministry of Communication and Digital Affairs of the Republic of Indonesia (Kemenkomdigi). IMDI is a composite index that measures the level of digital readiness and capacity of Indonesian society across four main dimensions: digital infrastructure and ecosystems, digital skills, community empowerment, and the use of technology in the workplace. The unit of analysis in this study is administrative regions at the provincial level in Indonesia. The data are cross-sectional in nature and represent the level of societal digital readiness in 2024.

Data Analysis Method

The data analysis method applied in this study is the K-means clustering approach. K-means is a non-hierarchical clustering method that aims to partition data into a specified number of clusters based on the degree of similarity among observations. Objects with high similarity are grouped into the same cluster, while dissimilar objects are assigned to different clusters, resulting in low within-cluster variation and relatively high between-cluster differences (Agusta, 2007).

Descriptive Data Analysis

Descriptive analysis is used to process and examine data through the stages of data collection, organization, presentation, and interpretation in the form of numerical values or percentages. The processed data are then presented in tables and graphs to facilitate understanding. This approach is applied to examine the overall characteristics of the data, thereby providing a clear overview and generating meaningful information for readers (Walpole, 1982).

Assumptions of Cluster Analysis

According to Hair et al. (2006), cluster analysis is a statistical technique that requires careful consideration of certain key factors to ensure that the resulting clusters are valid, reliable, and meaningful. In particular, there are two main considerations that researchers must take into account when performing cluster analysis, both of which are essential for producing clusters that accurately reflect the structure of the data and can be interpreted effectively, namely:

1. Representative Sample

   In cluster analysis, the data used must have an adequate level of representativeness so that the resulting clusters accurately reflect the characteristics of the population. The data analyzed may consist of population data or sample data, provided that the sample is capable of representing the underlying population. The absence of a strict standard regarding the minimum sample size considered representative encourages the use of a relatively large sample to enhance the reliability of the clustering process. The adequacy and representativeness of the sample can be evaluated using the Kaiser–Meyer–Olkin (KMO) test, which assesses overall sampling adequacy as well as adequacy at the level of individual indicators. KMO values range from 0 to 1, where values between 0.5 and 1 indicate that the data meet the adequacy criteria and are suitable for further analysis.

2. Non Multikolinearitas

   In addition to sample representativeness, another important assumption in cluster analysis is the absence of multicollinearity among variables. Multicollinearity refers to a condition in which strong linear relationships exist among variables, which may obscure the clarity of the resulting cluster structure. The presence of multicollinearity can be identified by examining the correlation coefficients among variables. According to Gujarati (2003), multicollinearity is considered to be present when the correlation coefficient exceeds 0.8. Therefore, cluster analysis should seek to minimize multicollinearity so that each variable contributes independent information to the clustering process. If multicollinearity cannot be avoided, one possible approach is to apply Principal Component Analysis (PCA) to reduce data dimensionality and mitigate inter-variable correlations prior to clustering.

Determination of the Number of Clusters

The determination of the optimal number of clusters in this study is conducted using the elbow method. This method is chosen due to its simplicity and effectiveness in identifying the most appropriate number of clusters in the K-means algorithm. The elbow approach evaluates changes in clustering error as the number of clusters increases, where the optimal point is indicated by the formation of an elbow-shaped pattern in the graph. This point represents the condition in which adding more clusters no longer results in a significant reduction in clustering error (Maldhulatha, 2012). The clustering error is calculated using the Sum of Squared Error (SSE), which measures the total squared distance between each data point and its corresponding cluster centroid. The SSE is computed using the following equation (Purwananto et al., 2012).

$$SSE = \sum_{k=1}^{k} \sum_{xi \epsilon sk} ||x_i - C_k||^2 \quad (1)$$

Notes:
k: Denotes the number of clusters used in the K-means algorithm
x_i: Represents the data points
C_k: Denotes the number of observations in the k-th cluster.

Analisis Cluster K-means

K-means is one of the non-hierarchical clustering methods used to group data into several clusters based on similarities in characteristics. Data points with similar properties are assigned to the same cluster, while dissimilar data points are placed in different clusters (Prasetyo, 2012). According to MacQueen (1967), the K-means clustering process begins by determining the desired number of clusters, denoted as k. The K-means clustering procedure can be described as follows:

1. Determining the number of clusters (k) to be formed.

   The selection of the number of clusters can be based on theoretical or conceptual considerations to obtain the most appropriate clustering structure.

2. Initializing the cluster centroids randomly.

   These initial centroids are selected from the existing data points according to the specified number of clusters (k). Subsequently, the centroid of the i-th cluster is calculated using the following formula:

$$C_{kj} = \frac{x1j + x2j + \cdots + xnj}{n} \quad (2)$$

Notes:
C_{kj}: Refers to the centroid of the k-th cluster for the j-th variable (j = 1, 2, …, p)
n: indicates the number of observations in the k-th cluster.

3. The next step is to calculate the distance between each observation and the centroid of each cluster. The distance between an observation and a centroid is measured using the Euclidean distance.

$$d\,(x, y) = \sqrt{(x_1 - y_1)^2} + \cdots + (x_p - y_p)^2 \quad (3)$$

4. Computing the Objective Function

$$J = \sum_{i=1}^{n}\sum_{j=1}^{k} a_{ij} d(x_i - C_{kj})^2 \quad (4)$$

Notes:
n: Denotes the number of observations;
k: Denotes the number of clusters
a_{ij}: Represents the membership value of data point
C_{kj}: epresents the membership value of data point
$d(x_i, C_{kj})$: denotes the distance between data point $x_i$and the corresponding cluster center

5. Assigning observations to the nearest centroid.
Each observation is allocated to the nearest centroid (mean) using the following rule:

$$aij = \begin{cases} 1, & if\ s\ =\ min\,\{d(x_i, C_{kj})\} \\ 0, & \end{cases} \quad (5)$$

Notes:

aij: Denotes the membership value of data point x_i to the cluster center C_{kj}

S: Represents the minimum distance from data point $x_i$to the cluster center.

6. Steps 3 to 6 are repeated until no observations change cluster membership or until there is no further change in the objective function.

Profiling Cluster

The elaboration of the clustering solution at this stage aims to illustrate the characteristics of each cluster in order to demonstrate that the clusters differ in meaningful aspects. The analysis focuses on characteristics that exhibit substantial differences across clusters and are capable of distinguishing the members belonging to a particular cluster (Supranto, 2004).

3. RESULT AND DISCUSSION

Descriptive Analysis

Descriptive analysis is an analytical method that involves the processes of data collection, processing, presentation, and interpretation of quantitative data or percentages represented in the form of tables or figures (Walpole, 1982). This descriptive approach is employed to examine the dataset with the aim of providing a comprehensive overview of the data, thereby facilitating clearer understanding and delivering meaningful information to readers.

Table 1. Descriptive Analysis

	Maximum	Minimum	Mean	Standar Deviasi	Skewnes	Kurtosis
Infrastructure and Ecosystem (IE)	72.11	31.59	52.70	8.03	-0.114	-.814
Digital Skills (DS)	65.56	45.83	58.25	3.83	-0.961	1.770

Empowerment (EPW)	38.80	19.57	26.05	2.98	1.723	8.846
Employment (EPL)	43.24	33.55	38.11	2.35	-0.051	-0.172

Descriptive statistical analysis conducted on the four pillars of the digital society index reveals some interesting differences. Infrastructure and Ecosystem has a fairly wide range of values, with a minimum of 31.59 and a maximum of 72.11. With a mean of 52.71 and a standard deviation of 8.03, there is a significant variation among participants. The skewness (-0.114), which is close to zero, indicates a relatively symmetrical distribution, while the positive kurtosis (0.814) suggests a distribution that is more "peaked" than a normal distribution.

Digital Skills shows better consistency compared to the other pillars, with the highest mean (58.25) and a smaller standard deviation (3.83). However, the high kurtosis (1.770) indicates the presence of outliers or extreme values, and the negative skewness (-0.961) shows that the distribution has a longer tail toward lower values.

Meanwhile, Empowerment exhibits lower variability with a standard deviation of 2.99 and the lowest mean (26.05). Nevertheless, the high positive skewness (1.723) indicates that most of the data are concentrated at lower values with a tail extending to the right. The distribution is highly "peaked" with significant outliers, as shown by the very high kurtosis (8.846).

Employment demonstrates a high level of homogeneity, with the narrowest value range of 9.69, a mean of 38.11, and a standard deviation of 2.25. With skewness (-0.051) close to zero and negative kurtosis (-0.172), the distribution is approximately normal but slightly "flatter" than a normal distribution.

Cluster Cluster Analysis Assumption Testing

Prior to conducting cluster analysis, two key assumptions must be satisfied. First, the population or sample size must be representative of the actual conditions being studied. Second, there should be no correlation among the research variables, as the presence of inter-variable correlations may affect the clarity and validity of the resulting cluster structure.

Data Adequacy and Variable Suitability Test

The first assumption requires that the sample size adequately represents the population. This assumption is tested using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy. The KMO statistic ranges from 0 to 1, where values between 0.5 and 1 indicate that the sample is considered representative and suitable for further analysis.

Table 2. Data and Variable Adequacy Test

		MSA (*Measure Sampling Adequacy*)
Overall		0,657
	IE	0,630
	DS	0,630
	EPW	0,758
	EPL	0,502

Based on Table 2, the overall KMO value for the four variables is 0.657, and the KMO values for each variable fall within the acceptable range of 0.5 to 1. These results indicate that the sample data are representative of the population and that all variables are suitable for cluster analysis.

Results of the Multicollinearity Test

The presence of multicollinearity among variables constitutes a violation in cluster analysis, as it may affect the resulting cluster structure. Multicollinearity testing is conducted to examine whether the variables are correlated with one another, or in other words, whether they share similar information, since good-quality data should be free from high inter-variable correlations. Multicollinearity is considered to exist when the correlation coefficient reaches or exceeds 0.8. In this study, the multicollinearity assumption is tested by examining the correlation coefficients among the variables.

Table 3. Multicollinearity Test

	IE	DS	EPW	EPL
IE	1	0,581	0,419	0,16
DA		1	0,420	0,086
EPW			1	0.46
EPL				1

Based on Table 3, all inter-variable correlation coefficients are below 0.8. Therefore, it can be concluded that multicollinearity is not present among the variables, indicating that the data satisfy the non-multicollinearity assumption required for cluster analysis.

Cluster Analysis Results

Since the Kaiser–Meyer–Olkin (KMO) and multicollinearity assumptions have been satisfied—indicating that the sample is representative and that no multicollinearity exists among the variables—the analysis can proceed to the cluster analysis stage.

Determination of the Number of Clusters

The determination of the number of clusters, or the value of *k*, can be specified directly by the researcher or determined using several approaches to obtain the optimal number of clusters. One commonly used approach is the elbow method, also known as the within-cluster sum of squares (WCSS) method. In applying the elbow method, the optimal value of *k* is identified at the point where the plot forms an elbow shape, indicating that additional clusters do not lead to a substantial reduction in within-cluster variation.

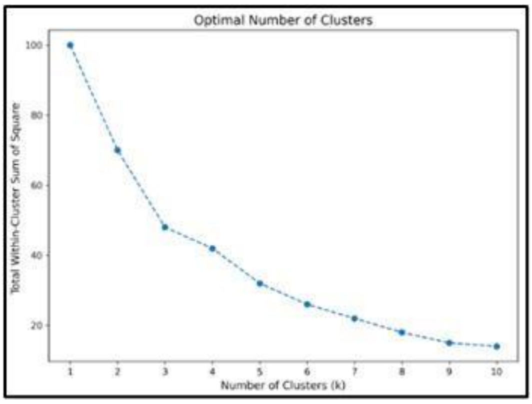

Figure 1. Determination of the Number of Clusters Using the Elbow Method

Figure 1 shows that the optimal value of *k* is three, as indicated by the formation of an elbow point in the cluster plot. Therefore, the optimal number of clusters obtained using the elbow method is three.

Cluster Membership

K-means cluster analysis requires the use of standardized data. Based on the optimal *k* value determined using the elbow or within-cluster sum of squares method, the Indonesian provinces are classified into three clusters according to IMDI data, as presented below.

Table 4. Anggota Klasterisasi IMDI di Indonesia

Cluster	Cluster Members
1	Aceh, Bengkulu, Sumatera Utara, Sumatera Selatan, Sumatera Barat, Sulawesi Utara, Jambi, Sulawesi Tenggara, Sulawesi Tengah, Sulawesi Selatan, Sulawesi Barat, Riau, Papua Barat Daya, Papua Barat, Papua, NTT, NTB, Maluku, Lampung, Kaltara, Kaltim, Kalteng, Kalbar, Gorontalo.
2	Maluku Utara, Papua Pegunungan, Papua Selatan, Papua Tengah.

3	Bali, Banten, DIY, DKI Jakarta, Kep. Riau, Kep. Babel, Kalimantan Selatan, Jawa Timur, Jawa Barat, Jawa Tengah

Based on Table 4, Cluster 1 consists of 24 provinces, Cluster 2 consists of 4 provinces, and Cluster 3 consists of 9 provinces.

Cluster Profiling

After determining the optimal number of clusters and their respective members, cluster profiling is conducted to identify the distinct digital readiness characteristics associated with each group. The profiling process is based on the mean values of four IMDI dimensions digital infrastructure and ecosystem, digital skills, digital empowerment, and employment calculated for each cluster. These dimensions jointly represent the structural and human capital foundations required for an inclusive digital economy across Indonesian provinces.

Table 5. Mean Values of Each Variable by Cluster

Variabel	**Cluster**		
	1	**2**	**3**
Infrastructure and Ecosystem	51,06	38,09	62,49
Digital Skills	58,37	51,86	60,54
Empowerment	25,96	22,64	27,64
Employment	38,21	37,31	38,18

Based on Table 5, the profiling results for provinces within the same cluster are obtained by examining the mean values of each variable across clusters. These mean values are then categorized into high, medium, and low levels. The highest mean values are classified as high, the second-highest as medium, and the lowest as low, as indicated by different shading intensities in the table. The following section presents the profiling results for each cluster based on the IMDI indicators in Indonesia:

Cluster 1 (Moderate Readiness with Relatively Strong Employment)

Cluster 1 is characterized by moderate levels of digital infrastructure and ecosystem, digital skills, and digital empowerment, accompanied by relatively higher employment outcomes. This pattern suggests that provinces in this cluster have begun to translate digital readiness into labor market participation, even though foundational digital capacities remain at an intermediate level. From an inclusive digital economy perspective, this cluster reflects regions with partial inclusion, where digital technologies contribute to employment but broader digital capabilities and empowerment have yet to fully mature.

Cluster 2 (Low Digital Readiness and Risk of Digital Exclusion)

Cluster 2 exhibits consistently low mean values across all IMDI dimensions, indicating limited digital infrastructure, weak digital skills, low community empowerment, and constrained employment opportunities. Provinces in this cluster face a high risk of digital exclusion, as insufficient digital readiness restricts their ability to participate in and benefit from the digital economy. These regions represent priority areas for inclusive digital policy interventions, particularly those aimed at improving digital infrastructure, enhancing human capital, and expanding digitally enabled employment opportunities.

Cluster 3 (High Digital Readiness and Inclusive Digital Potential)

Cluster 3 comprises provinces with the highest levels of digital infrastructure and ecosystem, digital skills, and digital empowerment, while employment outcomes are at a moderate level. This configuration reflects regions with strong digital foundations and high potential for inclusive digital economic development. Although employment levels have not yet reached the highest category, the robust digital capacity in this cluster suggests favorable conditions for future job creation and inclusive growth driven by digital transformation.

The results of the *K-Means* clustering and profiling are visualized using a thematic map to illustrate the spatial distribution of digital readiness clusters across regions.

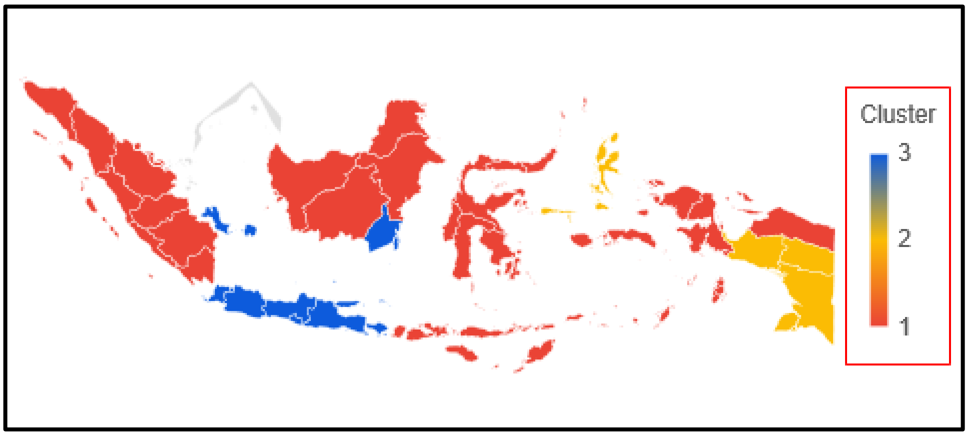

Figure 2. Mapping of Cluster Membership

Figure 2 illustrates the spatial mapping of provinces in Indonesia based on the Indonesian Digital Society Index (IMDI) for 2022. Provinces with a high level of digital readiness classified in Cluster 3 are represented in blue, provinces with a low level of digital readiness classified in Cluster 2 are shown in yellow, and provinces with a moderate level of digital readiness classified in Cluster 1 are depicted in red.

Based on this spatial distribution, provinces belonging to Cluster 2 can be identified as priority regions for enhancing digital readiness. The relatively low level of digital preparedness in this cluster indicates the need for more intensive policy interventions, particularly in strengthening digital infrastructure, improving digital skills among the population, and expanding the use of digital technologies in economic and employment-related activities.

By leveraging this spatial information, the government can formulate more targeted and region-specific digital development policies, allowing resources and digital transformation programs to be aligned with the distinct characteristics and needs of each cluster. Such an approach is expected to accelerate the reduction of interprovincial digital readiness disparities and support the development of a more inclusive digital economy in Indonesia.

4. CONCLUSION

This study applies *K-Means* clustering to the Indonesian Digital Society Index (IMDI) to assess digital readiness across provinces in Indonesia. The results classify provinces into three clusters: 10 provinces with high digital readiness, 24 provinces with moderate digital readiness, and 4 provinces with low digital readiness. Spatial analysis reveals significant regional disparities in digital readiness, particularly between highly prepared and less prepared regions. These findings highlight the importance of differentiated, region-specific digital development policies to reduce digital inequalities and promote an inclusive digital economy in Indonesia.

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