Sciencestatistics
Journal of Statistics, Probability, and Its Application
Available at https://scholar.ummetro.ac.id/index.php/sciencestatistics/index
DOI: https://doi.org/10.24127/sciencestatistics.v4i1.11486
Vol. 4, No. 1, 2026, 35-44
ISSN 2963-9875 (Online)
ISSN 2964-2884 (Print)

Application of Fuzzy C-Means with Variations in Weighting Exponent for Clustering the Human Development Index

Indah Suciati[1*], Rian Kurnia[2], Vina Nurmadani[3], Fitri Nurjanah[4]

[1*,2,3,4]Department of Data Science, Faculty of Science, Institut Teknologi Sumater, Lampung, Indonesia
*corresponding author: indah.suciati@sd.itera.ac.id

Article Info

Article History:
Received: January 05, 2026
Revised: January 15, 2026
Accepted: January 30, 2026
Available online: January 31, 2026

Keywords:
clustering;
fuzzy c-means;
human development index;
partition coefficient index;
weighting exponent.

ABSTRACT

Human development is commonly measured using the Human Development Index (HDI), which reflects the quality of life across regions. In Indonesia, disparities in HDI values indicate uneven development, requiring appropriate analytical approaches. This study aims to cluster Indonesian provinces based on HDI indicators using the Fuzzy C-Means (FCM) method with variations in the weighting exponent. The data consist of 38 provinces in 2025, including life expectancy, expected years of schooling, average years of schooling, and adjusted real expenditure per capita. The clustering results were evaluated using the Partition Coefficient Index (PCI). The optimal configuration was obtained at $k = 2$ and $m = 2$, with a PCI value of 0.716399. The results show that provinces are grouped into clusters with relatively lower HDI, which are predominantly located in eastern Indonesia, and clusters with higher HDI, which are mostly found in western Indonesia. These findings demonstrate that FCM is effective in identifying regional development patterns.

INTRODUCTION

Development is an effort to improve the quality of life of people in a region. In its implementation, development must be based on data analysis to plan and implement targeted policies, and evaluation is necessary to determine the effectiveness of development in improving human quality of life (Lie Darwin, 2022). Economic development is a crucial factor in improving human quality of life, reflected in increases in per capita income and purchasing power. However, development is not limited to economic aspects alone. In Indonesia, development disparities persist between regions, necessitating an indicator that can measure welfare levels more comprehensively (Damayanti & Mustakim, 2024). One key indicator to address this issue is the Human Development Index (HDI). This index is crucial in regional development planning because it provides a comprehensive picture of the community's quality of life (Todaro & Smith, 2020). The HDI can be measured through three fundamental components: health status, education quality, and access to economic resources, which includes equitable distribution of purchasing power (Jannah, Naeruz, & Amrani, 2025).

One approach that can be used to analyze these patterns is the clustering technique. Clustering is a method for grouping data that identifies groups (clusters) based on shared characteristics among smaller elements. This grouping is based on similarities between data elements, although these similarities are not universal (Anggraeni & Yudatama, 2023). Clustering methods such as conventional K-Means have limitations because each data item can only belong to one explicit cluster (hard clustering) and are weak in handling data with ambiguity or overlap between groups (Choudhary & Saxena, 2024). However, in the case of socio-economic data such as the HDI, a region can have characteristics that fall between several groups.

To overcome these limitations, the Fuzzy C-Means (FCM) method is used, a participant-based clustering method that utilizes a fuzzy logic approach (Fawas & Handhayani, 2025). The Fuzzy C-Means (FCM) algorithm offers a soft clustering approach, where each data item can have a degree of membership in more than one cluster. This allows for the intersection of data with mixed or transitional characteristics, such as socio-economic data between regions (Putra & Kurniawan, 2024). One important parameter in FCM is the weight exponent (m), which directly affects the fuzziness of the partition matrix and the resulting cluster assignments and plays a significant role in determining optimal clustering results. Despite the importance of this parameter, m is generally set to the default value of 2.0 without considering the specific characteristics of the dataset (Ismail, Seman, & Samah, 2025).

Similar to previous research by Razali, Puspaningrum, and Wahanani (2025), which applied the Fuzzy C-Means (FCM) method to the HDI in East Java regencies/cities, and research by Adnyani (2025), which applied the Fuzzy C-Means (FCM) method to the HDI in Papua Province. The study showed that this method is quite effective in clustering socio-economic data. However, the study still uses the default exponent weighting value (m) of 2.0 without further exploration of its value variations. Based on this, this study aims to apply the Fuzzy C-Means method with varying exponent weighting values to cluster HDI data in Indonesia. By comparing the results of these various parameter values, it is hoped that a better understanding of the structure of regional groups based on the level of human development can be obtained. Furthermore, the results of this study are also expected to serve as a basis for making more targeted development policies.

METHODS

Materials and Data

This study uses a quantitative approach to identify the clustering patterns of the Human Development Index (HDI) at the provincial level in Indonesia in 2025. The data used are secondary data sourced from the official publication of the Central Statistics Agency (BPS) in 2025. The dataset analyzed covers all 38 provinces in Indonesia, with the HDI constituent variables being life expectancy at birth (LEB), Expected Years of Schooling (EYS), Average Years of Schooling (AYS), and adjusted real expenditure per capita per year (EPC). All data processing and analysis processes are carried out using RStudio software, which supports various statistical analysis methods and numerical computations efficiently.

Research Methods

The method used in this research is Fuzzy C-Means (FCM), a fuzzy-based clustering technique that allows each object to have a level of involvement in more than one cluster. The analysis was conducted by considering variations in the exponent weight values and the number of iterations to test their influence on the clustering results.

The FCM method is a clustering approach in which each piece of data is not directly placed firmly into a specific cluster, but rather has a degree of membership in each cluster. This membership value is expressed as a real number ranging from 0 to 1, indicating how strongly the data belongs to a cluster. The higher the membership value, the greater the proximity of the data to the cluster center. This method was first introduced by Jim Bezdek in 1981 and is known to have a better ability to determine cluster centers more representatively than conventional clustering methods, because it takes into account the nature of data that is not always clearly separated (Megawati, Mukid, & Rahmawati, 2013).

In the clustering process, a measure is needed to determine the level of similarity or closeness between data. This measure is known as a distance measure (distance measure), which plays an important role in determining the unity of data relative to the cluster center. One of the most commonly used distance measures is the Euclidean distance, as it can represent the distance between data in a multidimensional space simply and comprehensively (Johnson & Wincern, 1982). The Euclidean distance formula used in this study is (Fathia, Rahmawati, & Tarno, 2016):

$$d_{ik} = \sqrt{\sum_{j=1}^{p} \left(x_{ij} - c_{kj}\right)^2} \quad (1)$$

where,

d_{ik} = Euclidean distance of the i-th object to the k-th cluster center
x_{ij} = data from the i-th object on the j-th variable
c_{kj} = k-th cluster center on j-th variable
n = number of data
p = number of variables
c = number of clusters
i = $1, 2, \dots, n$
j = $1, 2, \dots, p$
k = $1, 2, \dots, c$

This distance value then serves as the basis for determining the degree of data collection for each cluster in the Fuzzy C-Means (FCM) method. The smaller the distance of a data point from the cluster center, the greater the degree of protection for that cluster.

Based on the distance calculation obtained, the FCM algorithm is then run iteratively to update the cluster centers and membership degrees until convergence is achieved. In general, the FCM method steps refer to (Suciati et al., 2022) and begin with organizing the data into an $n \times p$ matrix $\boldsymbol{X}$, representing n objects and p variables.

Next, the initial parameters are determined, including the number of clusters $(1 < c < N)$, the weighting exponent $(m > 1)$, the maximum iteration $(MaxIter)$, the expected minimum error rate $(\varepsilon > 0)$, the initial value of the objective function $(P_0 = 0)$, and the initial iteration $(t = 1)$. After the parameters are set, an initial partition matrix $\boldsymbol{U}$ is formed containing the membership degrees μ_{ik}, which are randomly generated with values in the range 0 to 1. The initial partition matrix $\boldsymbol{U}$ formed is as follows:

$$\boldsymbol{U} = \begin{bmatrix} \mu_{11}(x_1) & \mu_{12}(x_1) & \cdots & \mu_{1c}(x_1) \\ \mu_{21}(x_2) & \mu_{22}(x_2) & \cdots & \mu_{2c}(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{n1}(x_n) & \mu_{n2}(x_n) & \cdots & \mu_{nc}(x_n) \end{bmatrix} \tag{2}$$

with the rule,

$$\sum_{k=1}^{c} \mu_{ik} = 1 \tag{3}$$

where μ_{ik} is initial partition matrix element $\boldsymbol{U}$ to-i of k-th cluster.
Based on the participant matrix, the cluster center v_{kj} is calculated for each variable by considering the membership degree weights assigned to the value m. For greater clarity, this is explained in Equation 4 as follows:

$$v_{kj} = \frac{\sum_{i=1}^{n}((\mu_{ik})^m x_{ij})}{\sum_{i=1}^{n}(\mu_{ik})^m} \tag{4}$$

where v_{kj} is the k-th cluster center value on the j-th variable. The results of this calculation produce a cluster center matrix $\boldsymbol{V}$, which is then used to calculate the objective function value at the t-th iteration. This objective function describes the total weighted error between the data and the cluster center based on the previously calculated distance. The cluster center matrix $\boldsymbol{V}$ is described in Equation 5, and the objective function formula is described in Equation 6 as follows:

$$\boldsymbol{V} = \begin{bmatrix} v_{11} & \cdots & v_{1p} \\ \vdots & \ddots & \vdots \\ v_{c1} & \cdots & v_{cp} \end{bmatrix} \tag{5}$$

$$P_t = \sum_{i=1}^{n} \sum_{k=1}^{c}((\mu_{ik})^m \, d_{ik}) \tag{6}$$

where P_t is the objective function value at iteration t. After that, the clustering degree value μ_{ik} is updated for each data set for each cluster, which is calculated based on the relative distance of the data set to all cluster centers. This membership value will change with each iteration following changes in the cluster centers. The formula for calculating the change in the membership matrix μ_{ik} is as follows:

$$\mu_{ik} = \left[\frac{\left[\sum_{j=1}^{p} d_{ik}\right]^{\frac{1}{m-1}}}{\sum_{k=1}^{c}\left[\sum_{j=1}^{p} d_{ik}\right]^{\frac{1}{m-1}}} \right]^{-1} \tag{7}$$

The iteration process is then continued by checking the stopping condition, namely if the difference in the objective function value between two consecutive iterations is smaller than the specified error limit ($|P_t - P_{t-1}| < \varepsilon$) or the number of iterations has exceeded the maximum limit ($t > MaxIter$). If the condition is not met, then the iteration continues by updating the value $t = t + 1$ and repeating the calculation process until a convergent result is obtained.

Once the FCM algorithm reaches convergence, the clustering process is considered complete in terms of determining the final cluster centers and membership degrees of each data point. However, the resulting clusters still need to be evaluated to assess their quality and to determine whether the formed cluster structure is optimal. This evaluation step is essential, particularly because different parameter settings, such as the number of clusters or weighting exponent, may produce varying clustering results.

To evaluate the clustering performance, a validity index is required. One of the commonly used indices in fuzzy clustering is the Partition Coefficient Index (PCI), which focuses on assessing the distribution of membership values generated by the FCM algorithm. The PCI is a cluster validity measure that evaluates clustering performance based solely on the membership degree values, without considering the distribution of the data or the positions of cluster centers (Wu & Yang, 2005). This index is particularly suitable for fuzzy clustering methods because it reflects how clearly each data point belongs to a specific cluster. The PCI measures the degree of fuzziness in the clustering results. A higher PCI value indicates that the membership values tend to be closer to 0 or 1, meaning that each data point is more distinctly assigned to a particular cluster. Conversely, a lower PCI value suggests that the membership degrees are more evenly distributed across clusters, indicating ambiguity in the clustering structure. The formula used to calculate the PCI is given as follows:

$$PCI = \frac{1}{n}\sum_{k=1}^{c}\sum_{i=1}^{n}(\mu_{ik})^2 \quad (9)$$

where n is the number of data objects, c is the number of clusters, and μ_{ik} represents the membership degree of the i-th object to the k-th cluster. The value of PCI ranges between 0 and 1.

In this study, the optimal number of clusters is determined based on the highest PCI value obtained from different clustering scenarios. Therefore, the PCI serves as an important criterion for selecting the most appropriate clustering configuration that best represents the underlying data structure.

RESULT AND DISCUSSIONS

This section presents the results obtained from the implementation of the Fuzzy C-Means (FCM) method, along with a comprehensive discussion of the findings. The analysis focuses on evaluating the clustering results under various parameter settings, particularly the number of clusters and the weighting exponent. Furthermore, the quality of the clustering outcomes is assessed using the Partition Coefficient Index (PCI) to determine the most optimal clustering configuration.

Data Pre-Processing

The data pre-processing stage was conducted to ensure data quality before the clustering process. At this stage, a check was performed for missing values to ensure the completeness of the data used in the analysis. Based on the check, no missing data was found, so all data could be used in the analysis. Next, the data was standardized using the z-score method to equalize the scales between variables, ensuring that each variable contributes equally to the clustering process and prevents dominance by any one variable. The following are some of the data standardization results used in this study in Table 1.

Table 1. Standardization of Human Development Index Data in Indonesia in 2025

Province	LEB	EYS	AYS	EPC
Aceh	0.1291302	1.10662384	0.74240176	-0.30375665
Sumatera Utara	0.4347384	0.23135707	0.84724638	-0.02585955
Sumatera Barat	0.6499554	1.01909716	0.59723229	0.03034877
⋮	⋮	⋮	⋮	⋮
Papua Pegunungan	-2.4233437	-3.19190854	-3.81430659	-2.39879415

Based on Table 1, the standardization results indicate that each variable is on the same scale, with an average approaching zero. Positive values indicate that a province has an indicator value above the national average, while negative values indicate conditions below average. For example, Aceh and West Sumatra provinces have several indicators with above-average values, while Highlands Papua shows values far below average across all indicators. This indicates a gap in human development between regions, which will form the basis for the clustering process.

Cluster Analysis Using the Fuzzy C-Means (FCM) Method

The clustering process using the FCM method is carried out through several stages. The first stage is constructing a 38×4 matrix, where the row component represents the number of provinces in Indonesia (38) and the column component represents the number of variables used (4). This matrix represents the standardized values of the research data collected in the previous process.

After obtaining the standardized data matrix, the next step is to determine the parameters used in the clustering process using the Fuzzy C-Means (FCM) method. These parameters include the number of clusters, weighting exponent, maximum iteration, error tolerance, initial objective function, and initial iteration. In this study, the number of clusters and the weighting exponent were not determined singly but were tested in several combinations of values, ranging from 2 to 5. This aimed to obtain optimal clustering results by comparing the various possible parameters used. The maximum iteration was set to 100 iterations, or until the process reached convergence, when the change in the objective function value was very small. The smallest error limit used was 10^{-9}, which served as the iteration termination criterion. Furthermore, the initial objective function value was set at zero as the initial condition before the iteration process began, while the initial iteration began from iteration 1. Determining these parameters is crucial because it will affect the convergence process and the quality of the clustering results produced by the Fuzzy C-Means method.

The next step is to construct the initial partition matrix $\boldsymbol{U} = [\mu_{ik}]$. This matrix is randomly generated, satisfying the condition $\sum_{k=1}^{c} \mu_{ik} = 1$ for each $i = 1, 2, \dots, 38$ and $k = 2, 3, 4, 5$, so that each object has a total membership degree of 1 across all clusters. The following is the initial partition matrix with 2 clusters, where each row of the matrix satisfies the membership degree of 1, as shown in Table 2.

Table 2. Example of an initial partition matrix for 2 clusters

Province	**Initial Partition Matrix**		**Total**
	Cluster 1	**Cluster 2**	
Aceh	0.4747395	0.5252605	1
Sumatera Utara	0.7729005	0.2270995	1
Sumatera Barat	0.7411997	0.2588003	1
⋮	⋮	⋮	⋮
Papua Pegunungan	0.4957495	0.5042505	1

Based on Table 2, the initial partition matrix in the clustering process with two clusters shows that each province has two membership degree values, each summing to 1. Next, to find the k-th cluster center for the j-th variable (v_{kj}), the membership degree of each object in that cluster can be calculated using the membership degree of each object for $k = 2, 3, 4, 5$ and $j = 1, 2, 3, 4$. This value represents the center point of each cluster, obtained as a weighted average of the data, with the weights being the membership degree. The results of the calculation of all v_{kj} form a cluster center matrix $\boldsymbol{V}$, which will be used in the next process. To calculate this cluster center, use the following equation.

$$v_{kj} = \frac{\sum_{i=1}^{38}((\mu_{ik})^m x_{ij})}{\sum_{i=1}^{38}(\mu_{ik})^m}.$$

The next step is to find the value of the objective function. The objective function value is used as the iteration termination criterion to obtain the optimal cluster center, calculated at the t-th iteration. This value represents the quality of the clustering, where a smaller P_t value indicates better clustering results. The iteration will stop if the absolute difference between the objective function values at the t-th and $(t-1)$-th iterations has reached a convergent condition. If this condition is not met, the iteration will continue. The next step is to calculate the change in membership values for each data item in each cluster. Once convergent values have been reached, the final change in membership values at the last iteration is used to determine whether a data item belongs to a particular cluster.

After convergence, the iteration will stop, and the next step is to cluster each object based on the final change in membership values for each item. In the clustering process, if an object's membership value in a particular cluster is greater than the membership values in other clusters, the object is more likely to be included in that cluster. In this study, the results of the clustering of the HDI data in Lampung Province for 2025, with a cluster size of 2 and a weighting exponent of 2, are presented in Table 3 below.

Table 3. Clustering of HDI data in Indonesia, with a cluster size of 2 and a weighting exponent of 2

Province	Cluster 1	Cluster 2	Data Tendency to Enter Clusters
Aceh	0.304584	0.695416	Cluster 2
Sumatera Utara	0.121041	0.878959	Cluster 2
Sumatera Barat	0.163248	0.836752	Cluster 2
⋮	⋮	⋮	⋮
Banten	0.045196	0.954804	Cluster 2
Bali	0.120992	0.879008	Cluster 2
Nusa Tenggara Barat	0.518113	0.481887	Cluster 1
⋮	⋮	⋮	⋮
Papua Selatan	0.885637	0.114363	Cluster 1
Papua Tengah	0.645056	0.354944	Cluster 1
Papua Pegunungan	0.632019	0.367981	Cluster 1

Based on Table 3. each province has a membership value for each cluster, indicating how strongly the province's data belongs to a cluster. For example, West Nusa Tenggara has a membership value of 0.518 in Cluster 1 and 0.482 in Cluster 2, indicating a higher data tendency in Cluster 1, thus placing this province in Cluster 1. The same applies to the provinces of South Papua, Central Papua, and Highland Papua, which have the highest membership values in Cluster 1, thus belonging to the cluster with a relatively lower HDI. Conversely, provinces such as Aceh, North Sumatra, West Sumatra, Banten, and Bali have the highest membership values in Cluster 2, thus belonging to the cluster with a higher HDI. Therefore, cluster determination is not based solely on a single category, but rather considers the degree of membership of each province within each cluster.

In this study, the Partition Coefficient Index (PCI) was used to determine the optimal number of clusters. In general, the optimal number of clusters is the one with the highest PCI value compared to other PCI values. In other words, if a cluster has the highest PCI value, then that number is chosen as the optimal number of clusters for clustering. A comparison of PCI values for the research data can be seen in Table 4.

Table 4. Comparison of PCI values

k	m	Objective Function	PCI Values
2	2	1.767809	0.716399
	3	0.935199	0.573794
	4	0.475992	0.531631
	5	0.239876	0.516298
3	2	1.16201	0.536057
	3	0.413708	0.386314
	4	0.140502	0.353478
	5	0.047217	0.344275
4	2	0.617184	0.60958
	3	0.232048	0.306635
	4	0.059295	0.275761
	5	0.014961	0.263797
5	2	0.460419	0.515874
	3	0.147985	0.258898
	4	0.030211	0.232979
	5	0.006097	0.227243

Based on Table 4 and PCI criteria, the optimal number of clusters for clustering HDI data in Indonesia is 2 with the weighting power used being 2.

Cluster Results Using the Fuzzy C-Means (FCM) Method

After determining the optimal number of clusters ($k = 2$) and the best weighting exponent ($m = 2$), Indonesian provinces were clustered based on the HDI, as shown in Table 5 below.

Table 5. Best cluster results using the FCM Method

Cluster	Number of Members	Province
1	14	Nusa Tenggara Barat, Nusa Tenggara Timur, Sulawesi Tengah, Sulawesi Tenggara, Gorontalo, Sulawesi Barat, Maluku, Maluku Utara, Papua Barat, Papua Barat Daya, Papua, Papua Selatan, Papua Tengah, dan Papua Pegunungan.
2	24	Aceh, Sumatera Utara, Sumatera Barat, Riau, Jambi, Sumatera Selatan, Bengkulu, Lampung, Kepulauan Bangka Belitung, Kepulauan Riau, DKI Jakarta, Jawa Barat, Jawa Tengah, DI Yogyakarta, Jawa Timur, Banten, Bali, Kalimantan Barat, Kalimantan Tengah, Kalimantan Selatan, Kalimantan Timur, Kalimantan Utara, Sulawesi Utara, dan Sulawesi Selatan

The results of clustering using the FCM method show that provinces in Indonesia are divided into two groups based on the similarity of HDI values. Cluster 1, consisting of 14 provinces, dominated by eastern Indonesia, such as Nusa Tenggara, Sulawesi, Maluku, and Papua, tends to have relatively lower HDI values. Meanwhile, Cluster 2, consisting of 24 provinces, the majority of which are located in western Indonesia, such as Sumatra, Java, and Kalimantan, shows relatively higher and more evenly distributed HDI values. This indicates a gap in human development between western and eastern Indonesia, where provinces within the same cluster have more homogeneous HDI characteristics than between clusters. To clarify the distribution pattern of clustering results based on these HDI characteristics, the following is a visualization map of provincial clusters in Indonesia.

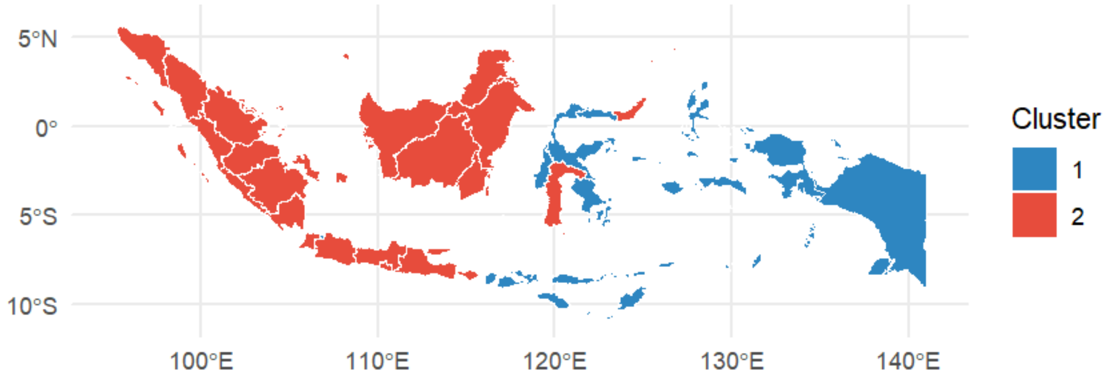

Figure 1. Map of the results of clustering provinces in Indonesia based on the HDI using the FCM method.

CONCLUSIONS AND SUGGESTIONS

Based on the results and discussion in this study, it was concluded that Based on the results and discussion in this study, it was concluded that the Fuzzy C-Means method is effective in grouping provinces in Indonesia based on the Human Development Index (HDI) in 2025. This study uses HDI constituent variables, namely life expectancy at birth (LEB), Expected Years of Schooling (EYS), Average Years of Schooling (AYS), and real expenditure per capita per year (adjusted) (EPC). In the analysis process, testing of variations in the number of clusters $k = 2$ to $k = 5$ and the weighting rank $m = 2$ to $m = 5$ using the Fuzzy C-Means method was carried out. Based on the evaluation using the Partition Coefficient Index (PCI) value, the best combination was obtained, namely $k = 2$ and $m = 2$ with a PCI value of 0.7163990, which indicates the most optimal cluster structure. The clustering results divide provinces in Indonesia into two main groups based on the characteristics of the HDI, where Cluster 1 is dominated by provinces with relatively lower HDI values which are generally located in the eastern part of Indonesia, while Cluster 2 consists of provinces with higher HDI values which are mostly located in the western part of Indonesia. Thus, the Fuzzy C-Means method is effective in grouping provinces based on the HDI which reflects the dimensions of health (LEB), education (EYS and AYS), and standard of living (EPC).

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