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Energy-Saving Behavior During the COVID-19 Pandemic in Indonesia: Do We Care?

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ABSTRACT

The COVID-19 pandemic has transformed people's lifestyles, including an increase in household energy consumption patterns due to work-from-home and distance learning policies. This study aims to identify household energy-saving behaviors in Indonesia during the pandemic and to classify provinces based on the level of these behaviors using clustering methods. The data were obtained from the Happiness Level Measurement Survey. The analyzed indicators include the use of energy-efficient light bulbs, turning off lights and televisions when not in use, utilizing natural daylight, and considering electricity consumption when purchasing electronic devices. K-Means and K-Medoids clustering methods were employed for analysis, with evaluations based on the Silhouette Index, Davies-Bouldin Index, and Calinski-Harabasz Index. The results indicate that the optimal configuration consists of three clusters, with the K-Medoids method showing greater robustness to outliers. In general, turning off unused electrical appliances is the most consistently practiced behavior, while energy efficiency considerations when purchasing electronics remain relatively low. These findings provide valuable insights for shaping post-pandemic household energy efficiency policies.

KEYWORDS: COVID-19 Pandemic; Energy-Saving Behavior; Cluster; K-Means; K-Medoids

INTRODUCTION

The COVID-19 pandemic, first emerging in China and officially reported in Indonesia in early March 2020 (Ratcliffe, 2020), has substantially altered various aspects of life, including household energy consumption patterns. Social restrictions and increased time spent at home compared to the pre-pandemic period (Mitra et al., 2022) shifted lifestyles, driving a direct increase in residential energy demand, particularly electricity (Novianto et al., 2022).

Energy plays a vital role in supporting economic growth, improving quality of life, and ensuring environmental sustainability. However, the increasing demand for energy has led to higher greenhouse gas emissions and environmental degradation. Therefore, energy efficiency has become a key focus in global sustainable development strategies (Bappenas, 2016). Based on SDGs 7 "Affordable and Clean Energy", the aim is to ensure access to affordable, reliable, sustainable, and modern energy for all. One of its main targets is to double the global rate of improvement in energy efficiency by 2030.

Data indicate that the residential sector accounted for approximately 16.36 percent of Indonesia's national energy consumption in 2021, representing a 2.79 percent increase from 2019 (ESDM, 2024). Household energy consumption is a critical concern due to its contribution to environmental change (Kerkhof et al., 2009), exacerbated by persistent energy-wasting habits, especially among middle- and high-income households, which remain difficult to modify (Mustapa et al., 2021). With Indonesia's population reaching 275 million and projected to grow steadily (BPS, 2023), energy demand is expected to rise significantly. Inefficient household energy use strains energy systems and intensifies greenhouse gas (GHG) emissions (Hertwich & Peters, 2009), with broader implications for the economy, environment, and climate (Seppälä et al., 2011).

During the pandemic, energy consumption shifted markedly, residential electricity use increased while other sectors declined (Takyi et al., 2023). Consequently, access to electricity became increasingly vital for daily home activities (Chen et al., 2020). The International Energy Agency (2020) emphasized that the pandemic presented a critical opportunity to accelerate energy efficiency strategies for climate change mitigation and net-zero emissions by 2050. Notably, in the Asia-Pacific region, residential and building sectors were the only ones exhibiting increased energy consumption during the pandemic, largely due to widespread work-from-home (WFH) policies (UNESCAP, 2021).

Several Indonesian studies have begun exploring these behavioral shifts. Novianto et al. (2015) identified housing characteristics, appliance ownership, and thermal energy use as dominant factors influencing household energy consumption in Indonesia, China, and Thailand. More recently, Novianto et al. (2022) found that WFH policies increased electricity usage across five major Indonesian islands, driven by household size, air conditioner use, and kitchen appliance usage. Similarly, Surahman et al. (2022) reported rising energy consumption in urban households during the pandemic, influenced by income, family size, and the number of electrical appliances.

Nevertheless, household energy consumption behavior in Indonesia during the COVID-19 pandemic remains underexplored. According to Ajzen (2005) Theory of Planned Behaviour, individual behavior is shaped by intention, which is influenced by behavioral, normative, and control beliefs, alongside personal, social, and informational factors. To date, no comprehensive study has specifically examined household energy consumption behavior during the pandemic from an energy efficiency perspective. Therefore, this study aims to identify indicators of energy-saving behavior among Indonesian households during the pandemic, and conduct a cluster analysis to group provinces based on household energy-saving behavior levels.

METHODOLOGY

Data Sources

The data source used in this study is the Happiness Level Measurement Survey 2021, which includes a total of 74,684 recovered sample households spread in 34 provinces throughout Indonesia.

Energy-Saving Behavior Framework

DEFRA (2008) focuses on behaviors that contribute to reducing carbon emissions, thereby supporting climate change mitigation efforts. The study examines pro-environmental behaviors that aim to protect and enhance the environment by encouraging greater participation in environmentally responsible actions by both individuals and communities. The DEFRA framework comprises five dimensions: (a) Personal transport, (b) Homes: waste, (c) Homes: energy, (d) Homes: water, and (e) Eco-products. This study specifically focuses on the "Homes: energy" dimension (DEFRA, 2009). This research focuses on analyzing several indicators related to household energy-saving behavior, including :

Table 1. Energy-Saving Behavior Indicators

Code	Indicator
(1)	(2)
X_1	Using energy-efficient light bulbs
X_2	Turning off lights when they are not needed
X_3	Utilizing natural daylight for indoor lighting during the day
X_4	Turning off the TV when not watching
X_5	Choosing electronic devices that use less electricity

Cluster Analysis

Cluster analysis identifies homogeneous groups within datasets while ensuring heterogeneity between groups (Everitt & Hothorn, 2011). As an exploratory technique, it requires no prior assumptions about cluster quantity or structure (Johnson & Wichern, 2002). This method reveals hidden data patterns by measuring similarity or distance between objects (Tan et al., 2006). In data mining, clustering simplifies complex datasets and detects patterns through feature similarity (Abualigah et al., 2018). Technological advances continue to drive the development of new clustering methods for emerging data challenges.

K-Means Clustering

K-Means partitions n observations into k clusters by minimizing intra-cluster variance (Witten et al., 2012). The algorithm assigns data points to predefined clusters, each represented by a centroid, the mean of cluster members (Kassambara, 2017). Through iterative centroid updates until convergence, K-Means serves as a widely-used tool for exploratory analysis and data segmentation (Han et al., 2012). The stages of forming clusters using the K-means clustering algorithm are as follows:

1. Determine the desired number of initial clusters (k).
2. Assign each object to the cluster with the closest mean, typically using Euclidean distance.
3. Recalculate the mean for clusters that gain or lose objects.
4. Repeat until no objects change clusters.

K-means clustering is sensitive to outliers, extreme distances, and noise. This is because observations that are far from the rest of the data can significantly shift the cluster mean, potentially leading to inaccurate clustering results.

K-Medoids Clustering

K-Medoids improves robustness against outliers by selecting actual data points (medoids) as cluster centers instead of centroids (Kaufman & Rousseeuw, 1990). This method minimizes the total absolute distance between medoids and other cluster points (Park & Jun, 2009), offering greater stability with noisy, non-Euclidean, or non-normally distributed data (Arora & Varshney, 2016). The steps of cluster formation using the K-medoids algorithm are as follows (Han et al., 2012):

1. Initiate or determine the desired number of initial clusters (k).
2. Assign each object to the cluster based on the representative object (medoid) with the nearest distance.
3. Randomly select a new object to serve as a medoid.
4. Use the new set of medoids to recalculate the total cost (total dissimilarity).
5. If the cost is less than 0, replace the j-th medoid with a randomly selected object from the dataset.
6. Repeat until there is no change in medoids (no objects switch clusters).

Clustering Assumptions

- **Bartlett's Test of Sphericity**
  Bartlett's Test of Sphericity is a statistical test used to determine whether the correlation matrix among indicators significantly differs from an identity matrix. An identity matrix implies no correlations among indicators. If the test result is significant (typically p-value < 0.05), it indicates that sufficient correlations exist among the indicators.
- **Kaiser-Meyer-Olkin (KMO)**
  The KMO test evaluates the adequacy of the sample by comparing the magnitude of observed correlation coefficients with partial correlation coefficients (OECD, 2008). A KMO value above 0.5 indicates that the data is suitable for this research.
- **Measure of Sampling Adequacy (MSA)**
  The Measure of Sampling Adequacy (MSA) assesses whether individual variables are appropriate for cluster analysis. According to Hair et al. (2010), a variable is considered suitable if its MSA value exceeds 0.5.

Model Evaluation

Optimal cluster count (k) was determined using three complementary metrics:

1. **Silhouette Coefficient:** Measures object similarity within its cluster versus other clusters (−1 to 1 scale). Higher values indicate superior cluster cohesion and separation (Rousseeuw, 1987).

$$S(i) = \frac{b_i - a_i}{\max(b_i, a_i)} \tag{1}$$

$$a_i = \frac{1}{n(C(i))} \sum_{j \in C(i)} dist\ (i,j) \tag{2}$$

$$b_i = min_{C_k \in C\ C(i)} \sum_{j \in C_k} \frac{dist\ (i,j)}{n(C_k)} \tag{3}$$

- S(i) is the Silhouette coefficient for object i, indicating how well the object fits within its own cluster compared to the nearest neighboring cluster
- a_i is the average distance between object i and all other objects in the same cluster.
- b_i is the average distance between object i and the objects in the nearest neighboring cluster.
- dist(i, j) is the dissimilarity distance between objects i and j (e.g., Euclidean, Manhattan, etc.).
- C(i) is the cluster that contains the i-th observation.
- n(C(i)) is the number of objects in cluster C(i) (cluster size).
- C_k is a cluster different from C(i), i.e., a neighboring cluster.
- $n(C_k)$ is the number of objects in cluster C_k.

2. **Davies-Bouldin Index (DBI):** Computes the average intra-cluster to inter-cluster distance ratio. Lower values denote compact, well-separated clusters (Davies & Bouldin, 1979).

$$DB = \frac{1}{k} \sum_{p=1}^{k} R_p \tag{4}$$

- DB is the Davies–Bouldin Index, a clustering validity index that evaluates how well clusters are separated and how compact they are. A lower DB value indicates better clustering performance.
- R_p is the maximum similarity measure between clusters, computed as the highest ratio between intra-cluster dispersion and inter-cluster distance.
- k is the total number of clusters formed.

3. **Calinski-Harabasz Index (CHI):** Evaluates the ratio of between-cluster to within-cluster dispersion. Higher values reflect optimal clustering with strong separation and homogeneity (Caliński & Harabasz, 1974).

$$CH = \frac{trace\ (SSB)}{trace\ (SSW)}\ x\ \frac{N-k}{k-1} \tag{5}$$

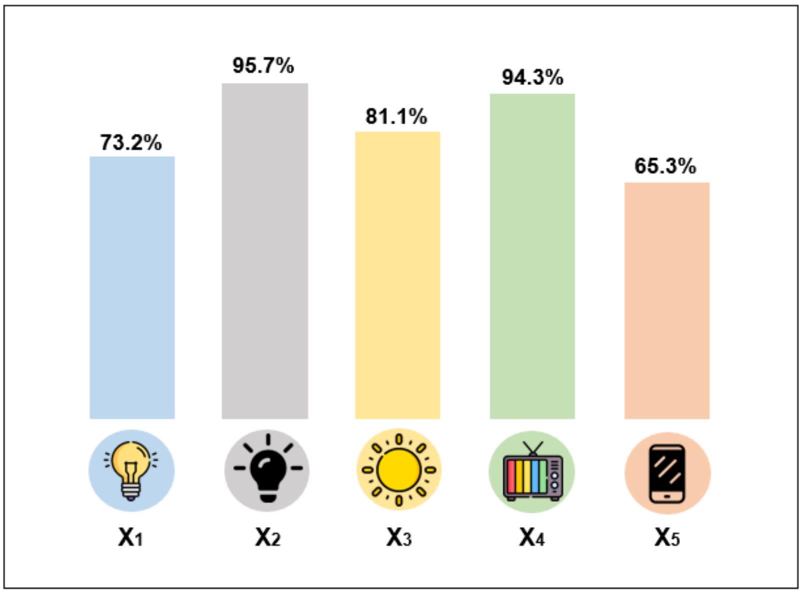
- CH is the Calinski–Harabasz Index, a clustering validity index that measures the ratio between the between-cluster dispersion and the within-cluster dispersion. A higher CH value indicates better clustering performance.
- SSB (Sum of Squares Between) is the between-cluster sum of squares, representing the variation between each cluster center and the overall data center.
- SSW (Sum of Squares Within) is the within-cluster sum of squares, representing the variation of data points within each cluster from their respective cluster centers.
- N is the total number of observations in the dataset.
- k is the total number of clusters formed.

RESULTS AND DISCUSSION

Overview of Energy-Saving Behavior in Indonesia

Household energy-saving behavior in Indonesia exhibits a relatively positive trend, as shown in **Figure 1**. Approximately 95.7 percent of households turn off lights when not in use, and 94.3 percent turno off the television when not watching, indicating a high level of awareness regarding daily energy conservation. In addition, 81.1 percent of households utilize daylight for indoor lighting, which not only reduces electricity usage but also aligns with sustainable building principles. The use of energy-efficient light bulbs was reported by 73.2 percent of households, suggesting that efficient technology has been widely adopted. However, only 65.3 percent of households consider electricity consumption when choosing electronic devices, indicating a continued need for public education on energy efficiency in consumer decision-making.

Figure 1. Overview of Energy-Saving Behavior in Indonesia

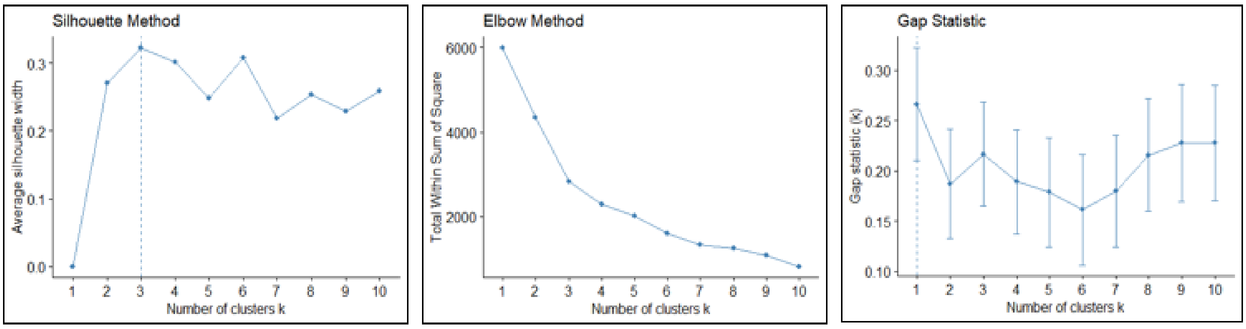


Cluster Analysis Results

The results of Bartlett's Test of Sphericity show a p-value less than 0.05, indicating that the correlation matrix is not an identity matrix and that there are significant correlations among the indicators. Furthermore, based on the results of the data processing, the Kaiser-Meyer-Olkin (KMO) value was greater than 0.5, indicating that the sample used in this study is adequate to represent the population in Indonesia. In addition, the Measure of Sampling Adequacy (MSA) for each indicator was also above 0.5, suggesting that the indicators are appropriate for prediction and further analysis using cluster analysis.

Based on **Figure 2,** the optimal number of clusters to distinguish household energy-saving behavior using the Silhouette method is three clusters. This result is further supported by the values of the Silhouette Index, Davies-Bouldin Index (DB Index), and Calinski-Harabasz Index (CH Index) obtained from both K-Means and K-Medoids clustering methods, as shown in **Table 2.**

Figure 2. The Optimal Number of Clusters



(a) Silhouette Method (b) Elbow Method (c) Gap Statistics

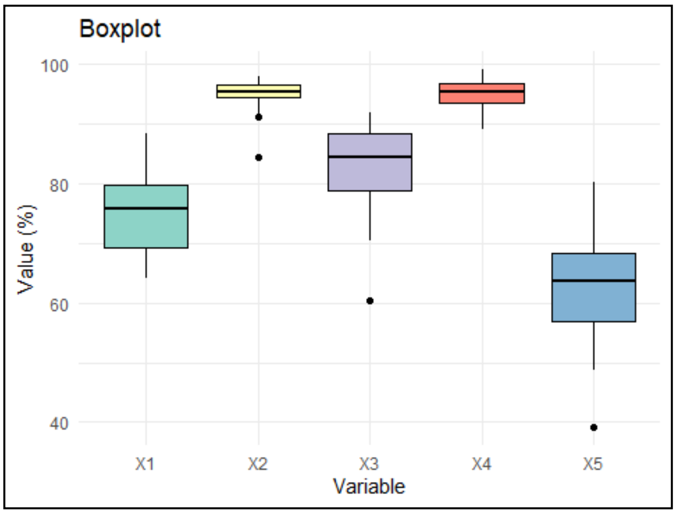
Table 2. Determination of the Optimal Number of Clusters

Cluster	K	Silhouette Index	Davies–Bouldin Index	Calinski–Harabasz Index
(1)	(2)	(3)	(4)	(5)
K-Means	2	0.2707945	1.324412	13.91873
	3	0.3221956	1.022908	17.21303
K-Medoids	2	0.2497579	1.412401	12.16966
	3	0.3022745	1.062849	15.88119

Source: Data processed

Evaluation of the K-Means and K-Medoids clustering methods using k = 2 and k = 3, assessed through the Silhouette Index, Davies–Bouldin Index (DB Index), and Calinski–Harabasz Index (CH Index), indicates that both methods perform optimally when k = 3. Nevertheless, given the presence of outliers in the data, as illustrated in **Figure 3**, the K-Medoids algorithm is deemed more appropriate, as it is more resilient to the influence of extreme values.

Figure 3. Boxplot of Energy-Saving Behavior Indicators



Based on the cluster analysis results presented in **Table 3,** provinces in Indonesia are grouped into three clusters according to the level of household energy-saving behavior. Cluster 1 consists of 8 provinces, representing regions with relatively better access to energy. Cluster 2 includes 14 provinces, indicating a relatively high but varied tendency toward energy-saving behavior. Meanwhile, Cluster 3 comprises 12 provinces, which generally exhibit lower levels of energy awareness. This clustering reflects differences in social, economic, and infrastructural characteristics across regions that influence household energy consumption behavior.

Table 3. Cluster Analysis Results

Cluster	Number	Cluster Members
(1)	(2)	(3)
1	8	Aceh, Kepulauan Riau, DKI Jakarta, West Java, East Java, Banten, Bali, East Kalimantan
2	14	North Sumatera, West Sumatera, Jambi, South Sumatera, Bengkulu, Lampung, Kepulauan Bangka Belitung, DI Yogyakarta, West Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, South Sulawesi, Southeast Sulawesi
3	12	Riau, Central Java, East Nusa Tenggara, North Kalimantan, North Sulawesi, Central Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, West Papua, Papua

Source: Data processed

Based on **Figure 4**, there are differences in the level of household awareness regarding energy-saving behavior across five key aspects. Cluster 1 is characterized by being "Aware" in using energy-efficient light bulbs, utilizing natural daylight for lighting, and considering low electricity consumption when buying electronic devices, and "Highly Aware" in turning off lights and TVs when not in use. Cluster 2 shows "Aware" behavior in using energy-efficient lighting, and "Highly Aware" in almost all other indicators, except for considering electricity usage when purchasing electronics, which is still at the "Moderately Aware" level. Meanwhile, Cluster 3 tends to show lower awareness, being only "Moderately Aware" in using energy-efficient lighting and considering electricity consumption, but still "Highly Aware" in turning off lights and TVs. This cluster analysis indicates that turning off electrical appliances when not in use is the most consistently applied energy-saving behavior across all clusters. In contrast, purchasing energy-efficient electronic devices remains relatively uncommon among most households.

Figure 4. Clusters of Energy-Saving Behavior in Indonesia

CONCLUSION

This study demonstrates that the COVID-19 pandemic had a significant impact on changes in household energy consumption behavior in Indonesia. Based on the K-Medoids analysis, provinces in Indonesia can be classified into three clusters according to their level of energy-saving behavior. Turning off electrical appliances when not in use emerged as the most commonly practiced action, while awareness of energy efficiency when purchasing electronic devices remains relatively low. These findings are expected to serve as a foundation for formulating policies that promote more widespread and sustainable energy-saving behavior in the post-pandemic period.

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