Research Article

Segmentation of Circular Economy Adoption in East Java-Indonesia Based on Barriers and Motivations Using K-Means and Multilayer Perceptron

[1]**Adnindya Krismahardi, [2,*]Alvionitha Sari Agstriningtyas, [3] Dhebys Suryani Hormansyah**

[1] Department of Environmental Health, Politeknik Kesehatan Kemenkes Surabaya, East Java, Indonesia
[2, 3] Department of Information Technology, State Polytechnic of Malang, East Java, Indonesia

* Corresponding Author: alvionithasara@polinema.ac.id

Abstract: The Circular economy is becoming increasingly relevant in addressing global challenges related to sustainability and natural resource management. While globally recognized, its implementation in East Java faces significant barriers, such as limited understanding, inadequate infrastructure, cultural resistance, and insufficient involvement from both the industrial sector and the public. This study aims to fill this gap by segmenting circular economy adoption in East Java based on motivations and barriers. Segmentation uses the K-Means algorithm combined with the Multilayer Perceptron (MLP) model. The analysis identifies three clusters: (1) highly motivated and proactive individuals, (2) moderately aware but less engaged individuals, and (3) individuals constrained by barriers and passive. The MLP model with 300 iterations delivered the best performance, achieving 92% accuracy, along with high precision and recall across all clusters. Chi-Square testing indicates that access to recycling, government support, and economic incentives significantly influence cluster formation, while product discounts and waste quantity have minimal impact. These findings provide insights for policymakers to design strategies to promote circular economy adoption, confirming that MLP is an effective tool for supporting.

Keywords: circular economy, k-means, multilayer perceptron, segmentation, East Java, barriers, motivation.

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1. Introduction

Circular economy has become an increasingly relevant concept amid global challenges related to sustainability and the management of limited natural resources[1]. It emphasizes reducing waste, maximizing reuse, repairing products, and recycling existing resources [2]. Fundamentally, the circular economy seeks to shift the conventional linear model of production and consumption toward a more regenerative system [3]. While the concept has gained global recognition, including in Indonesia, its implementation at the regional level—such as in East Java—continues to encounter substantial barriers [4][5]. In East Java, these challenges are influenced by factors such as limited understanding of long-term benefits, inadequate infrastructure, cultural resistance, and insufficient engagement from both the industrial sector and the public. Nationally, Indonesia faces similar issues, including weak regulatory frameworks and low awareness among both consumers and businesses [6][7]. Addressing these obstacles requires strong motivational drivers such as government incentives, consumer demand for sustainable products, and educational outreach [8]. However, despite growing academic attention to these factors, research that explicitly segments the adoption of circular economy practices based on motivations and barriers remains limited. To address this research gap, this study applies segmentation analysis to the adoption of the circular economy in East Java, emphasizing underlying motivations and constraints.

Segmentation serves a crucial role in this context by identifying distinct groups through appropriate analytical method [9]. The advancement of machine learning techniques further enhances segmentation capability by uncovering hidden patterns in behavioural data [10].

Previous studies have successfully applied such methods. For instance, [11] K-Means clustering to segment Hungarian food consumers based on awareness and purchasing behaviour, revealing that younger demographics exhibited more favourable attitudes toward circular economy practices. In the UK[12], a Choice-Based Conjoint method was used to segment 800 consumers into three distinct profiles based on their sensitivity to circular economy values. Other studies have adopted a hierarchical agglomeration approach followed by K-Means clustering for consumer segmentation, noting the efficiency and simplicity of K-Means despite its dependency on a predefined number of clusters [13]. Building upon this combination of K-Means and Multilayer Perceptron (MLP) methods has been widely proven to improve accuracy in segmentation and classification processes across various application domains. K-Means is effectively used to cluster data into homogeneous groups based on feature similarities, while MLP acts as an advanced classifier capable of generalizing and recognizing complex patterns from the clustering results. In a study on osteoporosis detection using dental radiographs, this approach achieved an accuracy of 90.48%, sensitivity of 90%, and specificity of 90.9% [14].

Similarly, in epilepsy detection based on EEG signals, the integration of K-Means, PCA, and MLP achieved a high accuracy of 98.98%, outperforming other algorithms such as SVM and Random Forest[15]. Another study on traffic conflict prediction demonstrated that K-Means effectively grouped driver behaviour patterns, which were then predicted accurately using MLP [16]. In the context of cancer subtype classification and Land Use Land Cover (LULC) mapping, MLP showed high performance when used after the segmentation process, achieving accuracy rates of 94.47% and 93,56% [17]. Even in household electricity load classification and plant disease prediction, MLP outperformed more than 10 other algorithms with accuracy rates exceeding 98% [18][19].

Furthermore, this combined approach has been used to segment mining images and classify recycling waste with highly accurate results [20]. Some studies also mention that K-Means is capable of breaking down non-linear structures, facilitating MLP training, and has advantages in reducing noise and enhancing model generalization [21]. However, several shortcomings of this approach have also been identified. First, K-Means is highly sensitive to the initial centroid initialization and requires the number of clusters to be pre-determined, which can affect results if not optimally set [22]. Additionally, MLP tends to require a large amount of training data to avoid overfitting, as well as high computation time to achieve optimal convergence [23]. The combination of these two methods also increases the complexity of the modelling pipeline, which requires thorough validation and testing of parameters to avoid classification or segmentation biases and misinterpretation. Therefore, while the combination of K-Means and MLP has proven to be robust and accurate in many contexts, its use still requires attention to configuration and parameter tuning to produce an optimal and reliable model.

By integrating K-Means and Multilayer Perceptron, this study seeks to address the research gap by providing a comprehensive segmentation of circular economy adoption in East Java. K-Means is effective in grouping respondents into homogeneous clusters based on similar perceptions, while MLP (Multilayer Perceptron) is capable of recognizing complex non-linear patterns from the segmentation results. This combination has been proven to yield high accuracy in various studies, like osteoporosis detection (98,98%) [14], epilepsy (98,98%) [15], and land use (94,47%)[24].

However, this approach has its drawbacks: K-Means is sensitive to initialization and the initial number of clusters, while MLP requires a sufficiently large dataset and careful parameter tuning to avoid overfitting. The complexity increases when the two methods are combined, thus requiring robust validation and evaluation. To address these challenges, this study implements several strategies: determining the optimal number of clusters using the Elbow Method and Silhouette Score; preprocessing through normalization and handling missing values; tuning MLP parameters using Grid Search, along with model regularization techniques and confusion matrix; and interpreting clusters based on social characteristics and respondent perceptions. With this approach, it is expected that the segmentation generated will provide an accurate and practical overview of the adoption of circular economy practices in East Java.

2. Theory

2.1 Circular Economy

The circular economy is an economic model that aims to maximize resource efficiency, reduce waste, and minimize environmental impact[25]. This model emphasizes sustainability by integrating principles such as recycling, business innovation that considers environmental aspects, and more responsible management of natural resources. In a circular economy, the primary focus is on maintaining the value of resources, minimizing excessive material consumption through redesigned processes and material cycles, and promoting responsible and sustainable consumption [26].

2.2 Theory of Planned Behaviour (TPB) Questionnaire

The Theory of Planned Behaviour (TPB) Questionnaire is a tool used to assess factors influencing an individual's intention to perform a specific behaviour. Based on the TPB framework, it focuses on three key elements: behavioural beliefs (attitudes toward the behaviour), normative beliefs (social pressure or subjective norms), and control beliefs (perceived ease or difficulty of performing the behaviour). These factors collectively form behavioural intentions, which are considered the immediate precursor to actual behaviour, provided there is sufficient control over the behaviour. The tool was modified and validated by an expert panel through content validation, assessing the clarity and relevance of the questionnaire items. This validation ensures that the questionnaire effectively measures professional attitudes, ethics, and behaviours [27][28].

2.3 K-Means Clustering

The K-means algorithm is a widely used clustering technique in data science that aims to divide a set of data points into a predefined number of clusters (K). The process begins by randomly selecting K data points to serve as initial cluster centroids. Each data point is then assigned to the cluster whose centroid is closest, typically based on the Euclidean distance. Next, the centroids are recalculated by finding the mean of all data points in each cluster. This process is repeated iteratively until the data points are consistently assigned to stable clusters.

In this approach, Euclidean distance is used to measure the distance between data points and their respective centroids, calculating the straight-line distance in a multidimensional space. The goal is to minimize the variance within each cluster, ensuring that similar data points are grouped while maximizing the dissimilarity between clusters [29], [30], [31].

2.4 Multilayer Perceptron

The Multi-Layer Perceptron (MLP) is a type of feed-forward neural network (FFNN) that contains one or more hidden layers, each consisting of one or more neurons. It is an extension of the perceptron network and is possibly the most widely used neural network model [32]. An MLP with a single hidden layer is referred to as a shallow neural network;

with a sufficient number of hidden neurons, a single hidden layer MLP can provide a universal approximation for nearly any problem involving tabular data. MLP is often used in combination with various methods, one of which is outlined in Table 1.

Table 1. MLP and Other Combinations

Methods	Description	Accuracy
MLP +DBSCAN	The developed system successfully provided an air pollution with selected features and trained Support Vector Machine (SVM) or Logistic Regression models[33].	81%,
MLP + GMM	Predicting consumer behaviour in Hungary and Iran [34].	96%
MLP + Random Forest	Predicting Pan Evaporation (Ep) in water resource management [35].	The Correlation Coefficient (CC) is 0.8704, the Scattered Index (SI) is 0.2539, and the Willmott's Index (WI) is 0.9212.

3. Method

The research method consists of stages, including surveys, preprocessing of responses, segmentation using K-Means clustering, classification using a Multilayer Perceptron Neural Network, and model evaluation using accuracy and other performance metrics.

3.1 Data Collection

Data were collected through questionnaires distributed to 165 respondents using Google Forms from various regions in East Java. The questionnaire was designed to capture demographic information such as gender, age, occupation, and education level, as well as respondents' perceptions regarding barriers, motivations, and behaviours in adopting circular economy practices. The perception-related items were measured using a five-point Likert scale, ranging from "Strongly Disagree (1)" to "Strongly Agree (5)".

The Likert scale, introduced by Rensis's [36] in 1932, is a commonly used psychometric tool in survey research to measure attitudes, opinions, or perceptions toward a given statement. It allows respondents to indicate their level of agreement on a symmetric agree–disagree scale, with each response assigned a numerical value. In this study, Likert-type items were grouped into constructs to form composite scales, which were treated as interval data. This enabled the use of parametric statistical methods for further analysis, supported by empirical evidence showing their robustness even under minor violations of statistical assumptions.

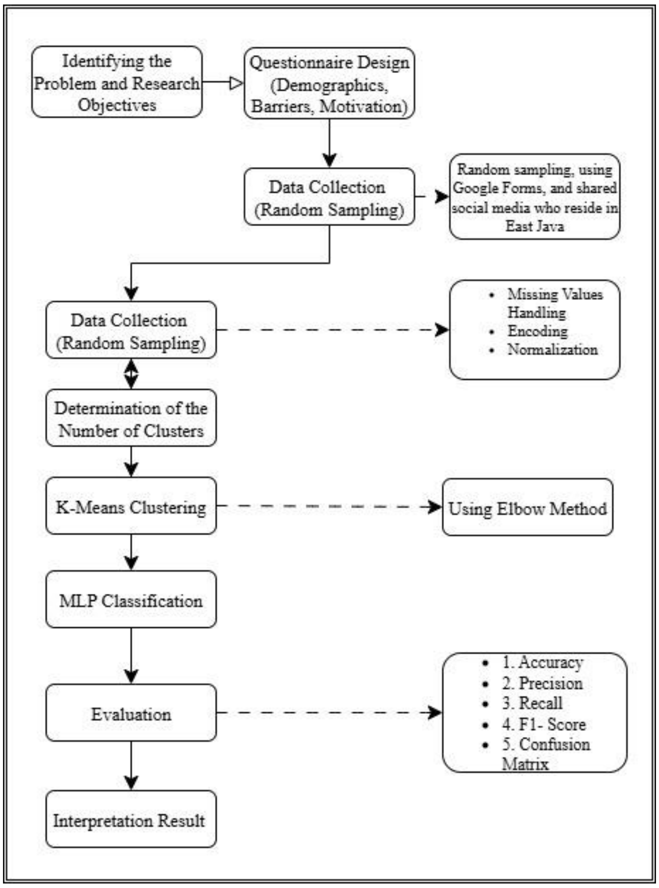

Figure 1. Sequential Steps Process

3.2 Questionnaire

The questionnaire is designed to identify the motivations and barriers faced by individuals in applying the principles of the circular economy, specifically related to the 3R principles (reduce, reuse, recycle). The primary goal of this questionnaire is to collect data that can be used to perform segmentation or clustering of individuals based on their attitude, knowledge, and behaviours toward the implementation of the circular economy.

The questionnaire consists of several sections that address the respondents' demographic aspect, their knowledge level regarding the circular economy, and the implementation of the 3R principles in daily life. Each question in the questionnaire is designed according to the Theory of Planned Behaviour, which includes the dimensions of attitudes, subjective norms, and perceived behavioural control, which are key factors in determining behavioural intentions and the application of the 3R principles. The first section of the questionnaire contains demographic questions aimed at identifying the respondents' background, such as age, highest level of education, and place of residence. This demographic data is important to understand whether there is a relationship between personal characteristics and the implementation of the circular economy.

The second section focuses on the level of implementation of the 3R principles in the respondents' daily lives. The questions aim to measure perceived behavioural control, which refers to the extent to which respondents feel they have the ability to apply the 3R principles in their lives. Additionally, some questions identify barriers or factors that influence the application of these principles.

The third section explores the respondents' knowledge of the circular economy. In this section, respondents are asked questions to measure their understanding of the principles of the circular economy and the 3R, including whether they understand the connection between the circular economy and waste management, as well as whether they are familiar with the 9R principles, which are an extension of the 3R principles.

The fourth section aims to determine the extent to which the respondents have applied the 9R principles. This section seeks to assess not only knowledge but also the actual practices undertaken by individuals related to the circular economy principles. Thus, the questionnaire will provide data that can be used to identify motivating factors and barriers in the application of the circular economy principles among individuals, which can then be used for cluster analysis based on the results from K-means clustering and MLP techniques.

Table 2. Questionnaire Structure Overview

Section	Topic	Purpose	Type of Question
I. Demographic	Name, Residence, Age, Last Education Level	To identify the personal characteristics of the respondents, to understand their influence on the application of the 3R	Open-ended and multiple-choice questions
2. 3R Implementation	Implementation of 3R in Daily Life	To measure the extent to which respondents apply the 3R principles, and identify barriers or hindering factors	Likert scale (Strongly agree to Strongly Disagree)
3. Circular Economy Knowledge	Knowledge about 3R and Circular Economy	To assess the respondents' knowledge level about the 3R, 9R principles, and their connection to waste management	Likert scale (Strongly agree to Strongly Disagree)
4. 9R Principles	Knowledge and Implementation of 9R Principles	To measure knowledge of the 9R principles in daily life, as well as barriers to their implementation	Likert scale (Strongly agree to Strongly Disagree)

Table 3. Questions Descriptions

No	Questionnaire
1	How often do you apply the 3R principles in your daily life?
2	What practices of reuse have you implemented in your daily life?
3	What factors influence someone in applying the 3R principles?
4	Are you familiar with the term "Circular Economy"?
5	Are you aware of the term "circular economy" in waste management?
6	If yes, are you familiar with the 9R principles of the circular economy?
7	Have you applied the 9R principles in your life?
8	Are you familiar with the term "3R"?

3.3 Data Preprocessing

Data preprocessing is crucial because it directly Data preprocessing is crucial because it directly affects the effectiveness and efficiency of the classification model. Handling missing values and data normalization are key preprocessing activities that ensure the data is in an optimal form for machine learning algorithms [37] [38]. Without proper preprocessing, models may produce inaccurate or biased results due to issues such as incomplete data or scale differences among variables [38][39].

a. Missing Value Handling
b. Encoding
c. Normalization

3.4 Clustering with K-Means

K-Means is a simple clustering analysis technique, aimed at finding the best way to divide entities into several groups called clusters [31]. In determining the optimal number of clusters, the Elbow Method is used for effective segmentation [40]. This process aims to group data into several clusters based on feature similarity. In using the Elbow Method, the number of clusters is selected at the elbow point of the inertia versus the number of clusters graph. This segmentation is useful for identifying hidden patterns in the data that can support the subsequent classification process. The distance between the data value and the cluster center value is expressed in Equation 1.

$$d(b_1, a_t) = \sqrt{\sum_{j=1}^{l}(b_{ij} - a_{tj})^2} \quad (1)$$

Where:

- *d = distance between data value and cluster centre value*
- $b_i = data\ \ value, i = 1,2, \dots, n, (n =$
$where\ \ n\ \ is\ \ the\ \ number\ \ of\ \ data\ \ points)$
- $a_t = cluster\ \ center\ \ value,\ (t = 1,2 \dots, K, K = number\ \ of\ \ cluster)$
- $l = number\ \ of\ \ attributes\ \ or\ \ dimensions$

3.5 Classification Using MLP

After the segmentation process, classification is performed using the Multilayer Perceptron (MLP) algorithm, an artificial neural network architecture consisting of input layers, hidden layers, and output layers [41]. MLP is chosen due to its ability to learn complex non-linear relationships between input features and cluster labels. The model is trained using the backpropagation and forward propagation algorithms [42] with the default optimization from the scikit-learn library. Parameters such as the number of neurons and iterations are set manually, and evaluation is based on prediction accuracy on the test data. The modelling process was conducted twice using different iteration settings: 300 and 500 iterations. The Multilayer Perceptron (MLP) model was employed to classify respondents into the predefined clusters. The dataset was divided into training and testing sets using the *train_test_split* method, with 70% allocated for training and 30% for testing. The MLP model was then trained and evaluated based on four performance metrics: accuracy, precision, recall, and F1-score.

3.6 Evaluation

To evaluate the performance of the classification model, several evaluation metrics are used: 1) Accuracy, which measures the proportion of correct predictions from the total data, 2) Precision, which shows the proportion of true positive predictions, 3) Recall, which indicates how well the model captures all positive data, and 4) F-1 Score, which is the harmonic mean of precision and recall. [43], [44]. The formulas for Accuracy, Precision, Recall, and F1-Score are shown in equations 2, 3, 4, and 5.

$$Accuracy : \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

$$Precision : \frac{TP}{TP+TP} \tag{3}$$

$$Recall : \frac{TP}{TP+FN} \tag{4}$$

$$F1-Score : \frac{2 \times precision \times recall}{precision+recall} \tag{5}$$

Where:
- *TP: True Positive*
- *TN: True Negative*
- *FN: False Negative*
- *FP: False Positive*

4. Result and Analysis

This study identifies the segmentation of circular economy adoption in East Java based on barriers and motivations, using a combination of K-Means for segmentation and Multilayer Perceptron (MLP) for classification. Data collected from various industries were analysed to determine key factors influencing adoption, with K-Means clustering businesses according to these factors, and MLP predicting the likelihood of successful adoption in each segment. The model evaluation shows a high accuracy (92%) in classification, indicating that MLP is capable of recognizing complex patterns from the results of K-Means segmentation. The findings reveal critical barriers such as financial constraints and regulatory issues, alongside motivations like cost savings and sustainability goals. The results are presented in the following Figure 2.

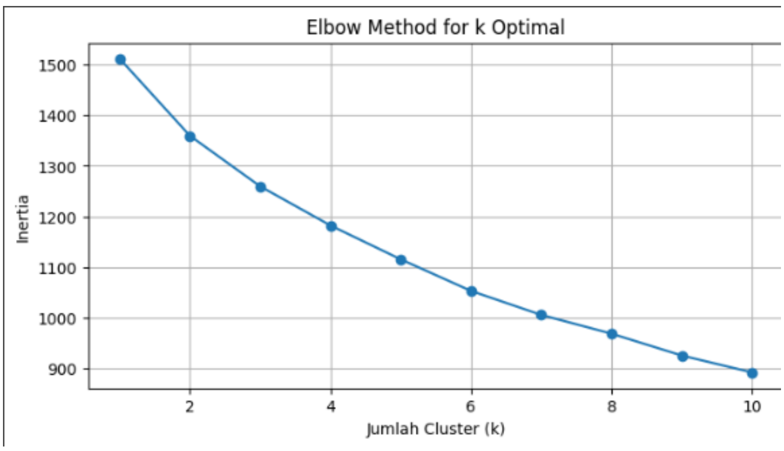

Figure 2. Elbow Methods Result

The following section presents the interpretation of the clusters obtained from the Elbow Method analysis in relation to circular economy adoption. This method was used to determine the optimal number of clusters, and the results are analysed to identify the distinct characteristics and behaviours within each group. The clusters reveal different patterns based on internal motivations and external barriers, highlighting the need for targeted interventions in circular economy campaigns.

- **Cluster 0** consists of individuals facing moderate barriers to accessing recycling facilities, with low internal motivation to engage in the circular economy. While this group may be aware of the benefits of the circular economy, they lack the personal drive necessary to actively adopt such practices.

- **Cluster 1** represents individuals with minimal barriers to accessing recycling facilities, high internal motivation, and strong behavioural intent toward adopting the circular economy. This group is the most proactive and receptive to sustainability practices, making them ideal candidates for roles as change agents or early adopters.

- **Cluster 2** includes individuals who encounter significant barriers, both financially and in terms of access to facilities, and exhibit low motivation to engage in circular behaviours. This segment is highly vulnerable and less involved, necessitating more intensive interventions, such as education, financial incentives, and improvements to infrastructure, to facilitate circular economy adoption.

Each cluster reflects a different combination of internal factors (motivation) and external factors (barriers and access), indicating that circular economy campaigns should be tailored to the specific needs of each group to maximize their effectiveness. The table in Figure 3 shows the average values of each motivation and barrier variable within the clusters resulting from the K-Means segmentation. Each cluster exhibits different value patterns, highlighting the unique characteristics of each group. For example, Cluster 1 shows the highest values for the variables of Supporting Factors and Circular Economy Adoption, while Cluster 2 shows relatively higher barriers in terms of cost and access.

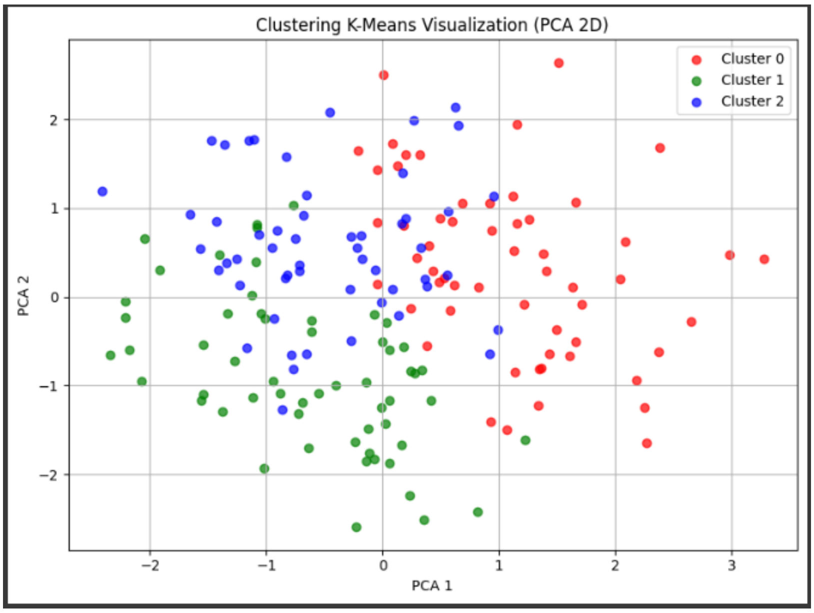

Figure 3. K-Means Visualization Clustering using PCA

Moreover, Figure 3 presents a two-dimensional visualization of the segmentation results using the K-Means algorithm, reduced through Principal Component Analysis (PCA). The points represent respondents, and the colours indicate the affiliation of each cluster. From this visualization, it can be seen that the clusters are fairly well-separated, particularly Cluster 1 and Cluster 2, which strengthens the validity of the segmentation.

Some overlap between points is still observed, reflecting similarities in characteristics at the cluster boundaries.

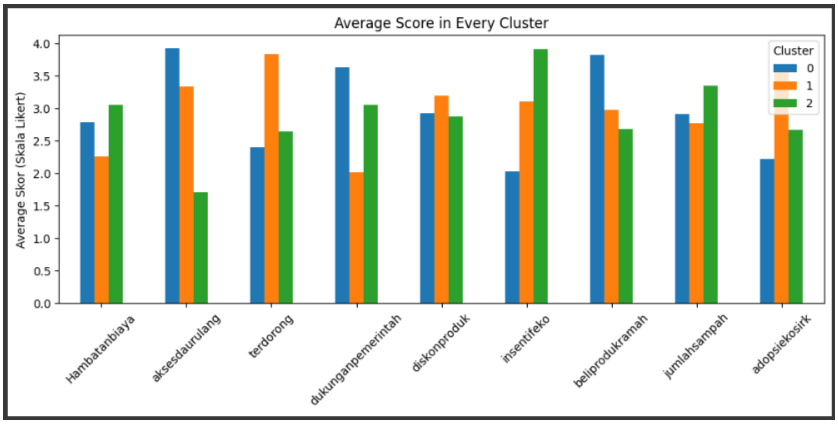

Figure **4.** Average Score Barriers and Motivation per Cluster

Based on the average scores of the nine perception variables measured on a Likert scale and grouped into three clusters, Cluster 0 has the highest average scores in the variables of access to circular economy products, external motivation, government support, easy access to information, and environmental behaviour awareness. As a result, they are more willing to implement circular economy processes in their lives. In Cluster 1, the highest scores were found in social support and balance, while the scores in other variables were moderate, suggesting that Cluster 1 consists of respondents with relatively high social motivation but who have not fully received adequate information or access related to the implementation of the circular economy. In the final cluster, Cluster 2, the results show the lowest scores across almost all variables, indicating limited access to information, support, and participation in circular economy activities.

Table 4. Cluster Centroids from K-Means Segmentation

Motivation and Barriers	**Cluster**		
	1	**2**	**3**
Cost Barriers	2,789474	2,263158	3,0555556
Recycling Access	3,929825	3,333333	1,703704
Driving Factors	2,403509	3,842105	2,648148
Government Support	3,631579	2,017544	3,0555556
Discounts Product	2,929825	3,192982	2,87037
Government Incentives	2,035088	3,105263	3,907407
Friendly Products	3,824561	2,982456	2,685185
Recycling Waste Quantity	2,912281	2,77193	3,351852
Circular Economy Familiar and Adoption Rate	2,22807	3,649123	2,666667

The results of the Chi-Square analysis show a significant relationship between certain features and the cluster groups. For example, the Recycling Access Level shows the highest Chi-Square value (18.183138, p-value = 0.000113), indicating that better access to recycling facilities is strongly associated with cluster selection. Other features, such as government incentives and support, influence the adoption patterns of individuals across different clusters. Meanwhile, other supporting factors, such as facilities or external motivations, also have varying impacts. The desire to adopt a circular economy holds the next position, so adoption behaviour influences the formation of clusters. Additionally, the availability of supporting facilities, as well as the lack of support, results in different adoption patterns in the implementation of the circular economy. However, factors such as the ability to purchase eco-friendly products, cost barriers, global waste amounts, and discounts on eco-friendly products do not have a significant impact on the formation of clusters. Chi-Square Score shown in Table 5.

Table 5. Chi-Square Score

No	Fitur	Chi_Score	p-value
1	Recycling Access	18.183138	0.000113
5	Government Incentives	12.270590	0.002165
3	Government Support	10.032709	0.006629
2	Motivating Factors	8.531726	0.014040
8	Circular Adoption	8.138306	0.017092
6	Buying Eco-Friendly Products	4.501230	0.105334
0	Cost Barriers	2.675946	0.262377
7	Amount of Waste	1.256603	0.533497
4	Product Discounts	0.413865	0.813075

From the K-Means segmentation, three main clusters are identified. Cluster 1 is the largest group, comprising 39.88% of the respondents, followed by Cluster 0 with 32.14%, and Cluster 2 with 27.98%. This proportion indicates that the majority of respondents belong to a group that is relatively ready to adopt circular economy practices, while others still face barriers or lack motivation. Response Percentages using K-Means Segmentations are shown in Table 6.

Table 6. Response Percentages using K-Means Segmentations

Cluster	Response Total	Percentage (%)
0	57	33.93
1	57	33.93
2	54	32.14

After segmentation, the Multilayer Perceptron (MLP) model was applied to classify individuals into the predefined clusters. Model evaluation was conducted using several performance metrics: precision, recall, and F1-score. Based on 500 iterations, the model achieved an overall accuracy of 89%, indicating that the model is quite effective in predicting the groups in circular economy adoption. However, despite the good accuracy, some classification errors were detected between Cluster 1 and Cluster 2, suggesting that there is overlap in behavioural characteristics between these two clusters. Table 7 is a Classification and Confusion Matrix Using 500 Iterations.

Table 7. Classification and Confusion Matrix Using 500 Iterations

	Precision	**Recall**	**F1-Score**	**Support**
0	0.88	0.88	0.88	17
1	0.79	0.88	0.83	17
2	1.00	0.88	0.94	17
accuracy			0.88	51
macro avg	0.89	0.88	0.88	51
weighted avg	0.89	0.88	0.88	51

Table 8. Confusion Matrix based on 500 Iterations

Predicted Class A	**Predicted Class B**	**Predicted Class C**
15	2	0
2	15	0
0	2	15

Tables 7 and 8 present the classification report and confusion matrix based on 500 iterations. The model's performance was evaluated using precision, recall, and F1-score, and the overall accuracy of the model was found to be 0.89. As indicated in the "accuracy" row, the model showed consistent performance across all classes. For individual classes, Class 0 achieved a precision of 0.88, a recall of 0.88, and an F1-score of 0.88, whereas Class 1 had slightly lower precision (0.79) but a recall of 0.88, resulting in an F1-score of 0.83. Class 2 displayed perfect precision (1.00), with a recall of 0.88, and an F1-score of 0.94, indicating strong performance in predicting this class.

Table 9. Classification and Confusion Matrix Using 300 Iterations

	Precision	**Recall**	**F1-Score**	**Support**
0	0.94	0.94	0.94	17
1	0.84	0.94	0.89	17
2	1.00	0.88	0.94	17
accuracy			0.92	51
macro avg	0.93	0.92	0.92	51
weighted avg	0.93	0.92	0.92	51

Table 10. Confusion Matrix based on 300 Iterations

Predicted Class A	**Predicted Class B**	**Predicted Class C**
16	1	0
1	16	0
0	2	15

Table 9 shows the Classification and Confusion Matrix Using 300 Iterations, while Table 10 shows the Confusion Matrix based on 300 Iterations. The macro and weighted averages for precision, recall, and F1-Score are all 0.89, reflecting consistent performance across the classes. These metrics suggest that the classification model can generalize well and distinguish between different clusters formed in the previous step of the analysis. The confusion matrix, displayed beneath the classification report, confirms the reliability of the predictions, with only a few misclassifications observed between Class 0 and Class 2. The results of the confusion matrix show that the model performs well overall with an accuracy of 89%, although a few small misclassifications were detected between Cluster 1 and Cluster 2. This indicates that the model can differentiate between the behaviour of different groups in circular economy adoption quite effectively.

In comparing both sets of results, it was found that the model's performance with 500 iterations provided a more reliable and consistent outcome. The accuracy of 0.89 and the precision-recall-F1-score values were stable across the iterations. Therefore, the best iteration for final evaluation was selected based on the 500 iterations, as it showed optimal classification results for distinguishing the clusters formed in the previous step of the analysis. Despite some minor misclassifications between Cluster 1 and Cluster 2, the model demonstrated a good ability to differentiate between the behaviour of different groups in circular economy adoption.

5. Discussion

The K-Means and MLP methods employed in this study have proven effective for segmentation and classification of circular economy adoption. However, several approaches can be considered to enhance the accuracy and reliability of the model. One such approach is to combine K-Means with other clustering algorithms, such as DBSCAN or Gaussian Mixture Model (GMM), which are better suited to handle data with more complex distributions. Additionally, MLP can be replaced or integrated with explainable AI (XAI) approaches based on deep learning to improve the transparency of classification. The use of hybrid or ensemble methods that combine multiple algorithms could address the shortcomings of each method, resulting in a more robust model capable of handling data variability.

On the other hand, to enhance the validity of the questionnaire, a more thorough testing of the instruments used is required. One way to achieve this is by conducting more comprehensive validity and reliability tests, such as factor analysis, to ensure that each item in the questionnaire measures the intended constructs. Stricter testing of the items in the questionnaire will also strengthen the accuracy of the collected data, thus ensuring that the results of segmentation and classification more accurately represent the studied population.

6. Conclusion

This study successfully segmented circular economy adoption behaviour in East Java, Indonesia, using the K-Means clustering algorithm based on barriers and motivational factors. The analysis revealed that the optimal number of clusters was $k = 3$, resulting in three distinct respondent groups: (1) highly motivated and proactive individuals, (2) moderately aware but less engaged individuals, and (3) those constrained by limitations and showing passive behaviour. Each segment reflects a unique combination of internal and external factors, indicating that circular economy strategies should be adapted accordingly—through educational campaigns, empowerment programs, or structural support mechanisms.

Moreover, to automate the classification of new respondents, a Multilayer Perceptron (MLP) algorithm was employed to predict cluster membership based on individual attributes. The MLP model with 300 iterations delivered the best performance, achieving 92% accuracy, along with high precision and recall across all clusters. These results confirm that MLP is an effective tool for supporting accurate and scalable segmentation in social and behavioural contexts.

Furthermore, a Chi-Square statistical test demonstrated that variables such as access to recycling, government support, and economic incentives had a significant influence on cluster formation. Conversely, factors such as product discounts and waste quantity were found to have minimal impact. This highlights the critical role of motivational and structural enablers in promoting circular economy adoption.

Finally, in conclusion, this study offers a data-driven framework for understanding public segmentation in circular economy initiatives, providing strategic insights for policymakers and environmental stakeholders. Future research can be expanded by integrating spatial data, behavioural tracking, or longitudinal methods to observe change over time.

7. Future Work

After the technical optimization of the segmentation and classification modelling has been successfully carried out, the next development direction can focus on expanding the application and integrating this approach into public policy and decision-making systems. One important direction is the integration of behaviour-based segmentation with spatial and macro socio-demographic data to build an adaptive and location-specific policy recommendation system.

Additionally, future research could explore the use of hybrid or ensemble methods, such as combining K-Means with other clustering algorithms like DBSCAN or GMM, and replacing MLP with explainable AI (XAI) approaches based on deep learning to make the classification more transparent. On the other hand, a longitudinal approach could also be applied to observe segmentation changes over time, thus enabling the evaluation of the effectiveness of implemented intervention programs or policies.

Future research could also integrate primary data from respondents with secondary data, such as environmental indices, waste management facility distribution, or regional regulations, to build a more holistic circular economy adoption readiness mapping system. This development will not only strengthen the predictive power of the model but also support more strategic and inclusive data-driven decision-making at the regional level.

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References

[1] N. F. Islam, B. Gogoi, R. Saikia, B. Yousaf, M. Narayan, and H. Sarma, "Encouraging circular economy and sustainable environmental practices by addressing waste management and biomass energy production," Reg. Sustain., vol. 5, no. 4, 2024, doi: 10.1016/j.regsus.2024.100174.
[2] Elma Sibonghanoy Groenewald, "Circular Economy Strategies in Supply Chain Management: Towards Zero Waste," Power Syst. Technol., vol. 48, no. 1, pp. 464–480, 2024, doi: 10.52783/pst.291.
[3] J. Kirchherr, N. H. N. Yang, F. Schulze-Spüntrup, M. J. Heerink, and K. Hartley, Conceptualizing the Circular Economy (Revisited): An Analysis of 221 Definitions, vol. 194, no. July. 2023. doi: 10.1016/j.resconrec.2023.107001.
[4] B. Kementerian PPN, "Peta Jalan dan Rencana Aksi Ekonomi Sirkular Indonesia," 2025.
[5] Bappelitbang, "Kajian Perencanaan Integrasi Lingkup Perekonomian," pp. 1–23, 2023.
[6] A. F. Larasati and E. B. Santoso, "Faktor-Faktor yang Mempengaruhi Transisi Ekonomi Sirkular Dalam Pengelolaan Sampah Rumah Tangga di Kota Surabaya," J. Penataan Ruang, vol. 18, p. 9, 2023, doi: 10.12962/j2716179x.v18i1.17229.
[7] M. Quraisy, "Analisis Hambatan Dan Keterbatasan Implementasi Ekonomi Sirkular Di Industri Manufaktur Indonesia : Studi Literatur dan Rekomendasi Kebijakan," J. Ekon. Manaj., vol. 15(2), no. February, pp. 123–138, 2025, doi: 10.13140/RG.2.2.20827.07208.
[8] H.-M. Voigt, "1. Introduction," Evol. Optim., vol. 31, no. 1, pp. 11–16, 2022, doi: 10.1515/9783112568620-002.
[9] T. Ritter and C. L. Pedersen, Is segmentation a theory? Improving the theoretical basis of a foundational concept in business-to-business marketing, vol.116, no. January. 2024. doi: 10.1016/j.indmarman.2023.11.012.
[10] I. U. Sayan, M. Demirdag, G. Yuceturk, and S. M. Yalcinkaya, "A Review of Customer Segmentation Methods: The Case of Investment Sector," 5th Int. Conf. Big Data Artif. Intell. BDAI 2022, no. September, pp. 200–204, 2022, doi: 10.1109/BDAI56143.2022.9862801.
[11] K. N. Pércsi, A. Ujj, and P. Jancsovszka, "Segmentation of Hungarian Consumers Based on Circular Economy Values and Awareness of Food Waste," Sustain., vol. 15, no. 11, pp. 1–18, 2023, doi: 10.3390/su15118838.
[12] R. H. W. Boyer, A. D. Hunka, and K. A. Whalen, "Consumer Demand for Circular Products : Identifying Customer Segments in the Circular Economy," 2021.
[13] D. Jendza, "Leader vs team member - Differences in equality and hierarchical individualism and collectivism - the context of public and private organisations," Management, vol. 28, no. 2, pp. 185–205, 2024, doi: 10.58691/man/195476.
[14] R. Widyaningrum, E. I. Sela, R. Pulungan, and A. Septiarini, "Automatic Segmentation of Periapical Radiograph Using Color Histogram and Machine Learning for Osteoporosis Detection," Int. J. Dent., vol. 2023, pp. 1–20, 2023, doi: 10.1155/2023/6662911.
[15] K. M. Alalayah, E. M. Senan, H. F. Atlam, I. A. Ahmed, and H. S. A. Shatnawi, "Effective Early Detection of Epileptic Seizures through EEG Signals Using Classification Algorithms Based on t-Distributed Stochastic Neighbor Embedding and K-Means," Diagnostics, vol. 13, no. 11, pp. 1–24, 2023, doi: 10.3390/diagnostics13111957.
[16] Y. Yuan, X. Wang, S. Calvert, R. Happee, and M. Wang, "A risk-based driver behaviour model," IET Intell. Transp. Syst., vol. 18, no. 1, pp. 88–100, 2024, doi: 10.1049/itr2.12435.
[17] Y. Wang, Y. Sun, X. Cao, Y. Wang, W. Zhang, and X. Cheng, "A review of regional and Global scale Land Use/Land Cover (LULC) mapping products generated from satellite remote sensing," ISPRS J. Photogramm. Remote Sens., vol.206, no. December, pp. 311–334, 2023, doi: 10.1016/j.isprsjprs.2023.11.014.
[18] S. Afzal, B. M. Ziapour, A. Shokri, H. Shakibi, and B. Sobhani, "Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms," Energy, vol. 282, no. November, pp. 1–9, 2023, doi: 10.1016/j.energy.2023.128446.
[19] B. M. Patil and V. Burkpalli, "Performance evaluation of the classifiers based on features from cotton leaf images," Multimed. Tools Appl., pp. 1–5, 2025, doi: 10.1007/s11042-025-20670-z.
[20] N. Haqiq, M. Zaim, M. Sbihi, M. El Alaoui, L. Masmoudi, and H. Echarrafi, "An improved mining image segmentation with K-Means and morphology using drone dataset," Int. J. Electr. Comput. Eng., vol. 14, no. 3, pp. 2655–2675, 2024, doi: 10.11591/ijece.v14i3.pp2655-2675.
[21] D. Pardede, A. Ichsan, and S. Riyadi, "Journal of Computer Networks, Architecture and High Performance Computing Enhancing Multi-Layer Perceptron Performance with K-Means Clustering Journal of Computer Networks, Architecture and High Performance Computing," vol. 6, no. 1, pp. 461–466, 2024.

[22] A. T. Cui Chenghu, "A Novel Classification Model Based on Hybrid K-Means and Neural Network for Classification Problems," HighTech Innov. J., vol. 5, 2024.
[23] D. T. Li Shen, Yan Sun, Zhiyuan Yu, Liang Ding, Xinmei Tian, "On Efficient Training of Large-Scale Deep Learning Models," ACM Comput. Surv., vol. 57, no. 3, 2024.
[24] C. Valdivieso-Ros, F. Alonso-Sarría, and F. Gomariz-Castillo, "Impact of segmentation algorithms on multisensor LULC classification in a semiarid Mediterranean area," Earth Sci. Informatics, vol. 16, no. 4, pp. 3861–3883, 2023, doi: 10.1007/s12145-023-01124-2.
[25] V. Radivojević, T. Rađenović, and J. Dimovski, "The Role of Circular Economy in Driving Economic Growth: Evidence from EU Countries," SAGE Open, vol. 14, no. 4, pp. 1–11, 2024, doi: 10.1177/21582440241240624.
[26] E. Safariyani and E. Taufiqurahman, "the Influence of the Circular Economy on Economic Growth: Literature Review," Eksis J. Ris. Ekon. dan Bisnis, vol. 17, no. 2, pp. 183–196, 2023, doi: 10.26533/eksis.v17i2.1102.
[27] S. S. Guraya et al., "Validating a theory of planned behavior questionnaire for assessing changes in professional behaviors of medical students," Front. Med., vol. 11, no. May, pp. 1–8, 2024, doi: 10.3389/fmed.2024.1382903.
[28] I. Ajzen, "Constructing a theory of planned behavior questionnaire," Biofeedback and selfregulation, vol. 17, no. March, pp. 1–7, 2010, doi: 10.1016/0749-5978(91)90020-T.
[29] Emigawaty, K. Adi, A. F. Rochim, B. Warsito, and A. Wibowo, "K-Means Clustering Algorithm for Partitioning the Openness Levels of Open Government Data Portals," Int. J. Informatics Vis., vol. 7, no. 3, pp. 977–983, 2023, doi: 10.30630/joiv.7.3.1761.
[30] K. P. Sinaga and M. S. Yang, "Unsupervised K-means clustering algorithm," IEEE Access, vol. 8, pp. 80716–80727, 2020, doi: 10.1109/ACCESS.2020.2988796.
[31] E. A. Saputra and Y. Nataliani, "Analisis Pengelompokan Data Nilai Siswa untuk Menentukan Siswa Berprestasi Menggunakan Metode Clustering K-Means," J. Inf. Syst. Informatics, vol. 3, no. 3, pp. 424–439, 2021, doi: 10.51519/journalisi.v3i3.164.
[32] A. Al Bataineh, D. Kaur, and S. M. J. Jalali, "Multi-Layer Perceptron Training Optimization Using Nature Inspired Computing," IEEE Access, vol. 10, pp. 36963–36977, 2022, doi: 10.1109/ACCESS.2022.3164669.
[33] G. Moheshkumar, N. Saravanan, T. Ravichandru, C. Tharun, and M. Subash Chandra Bose, "Revolutionizing Air Quality Prognostication: Fusion of Deep Learning and Density-Based Spatial Clustering of Applications with Noise for Enhanced Pollution Prediction," Proc. - 2024 4th Int. Conf. Pervasive Comput. Soc. Networking, ICPCSN 2024, pp. 124–129, 2024, doi: 10.1109/ICPCSN62568.2024.00029.
[34] A. Salamzadeh, P. Ebrahimi, M. Soleimani, and M. Fekete-Farkas, "Grocery Apps and Consumer Purchase Behavior: Application of Gaussian Mixture Model and Multi-Layer Perceptron Algorithm," J. Risk Financ. Manag., vol. 15, no. 10, 2022, doi: 10.3390/jrfm15100424.
[35] S. Shadkani, S. Hashemi, A. Pak, and A. B. Lahijan, "Random Forest and Multilayer Perceptron hybrid models integrated with the genetic algorithm for predicting pan evaporation of target site using a limited set of neighboring reference station data," Earth Sci. Informatics, vol. 17, no. 2, pp. 1261–1280, 2024, doi: 10.1007/s12145-024-01237-2.
[36] A. Joshi, S. Kale, S. Chandel, and D. Pal, "Likert Scale: Explored and Explained," Br. J. Appl. Sci. Technol., vol. 7, no. 4, pp. 396–403, 2015, doi: 10.9734/bjast/2015/14975.
[37] P. Yasodha, "Data Preprocessing Methods for Machine Learning : An Empirical Comparison," Int. J. Multidiscip. Res., pp. 2–5, 2025.
[38] E. Alshdaifat, D. Alshdaifat, A. Alsarhan, F. Hussein, and S. Moh, "The Effect of Preprocessing Techniques , Applied to Numeric, on Classification Algorithms Performance," Data, vol. 6, no. 11, 2021.
[39] K. Maharana, S. Mondal, and B. Nemade, "A review: Data pre-processing and data augmentation techniques," Glob. Transitions Proc., vol. 3, no. 1, pp. 91–99, 2022, doi: 10.1016/j.gltp.2022.04.020.
[40] J. Wala, H. Herman, R. Umar, and S. Suwanti, "Heart Disease Clustering Modeling Using a Combination of the K-Means Clustering Algorithm and the Elbow Method," Sci. J. Informatics, vol. 11, no. 4, pp. 903–914, 2024, doi: 10.15294/sji.v11i4.14096.
[41] P. Marius-Constantin, V. E. Balas, L. Perescu-Popescu, and N. Mastorakis, "Multilayer perceptron and neural networks," WSEAS Trans. Circuits Syst., vol. 8, no. 7, pp. 579–588, 2009, doi: 10.1002/9781394268993.ch3.
[42] S. Shinde and S. Kadam, "Multilayer Perceptron Neural Network Based Recognition of," no. February 2022, 2023, doi: 10.11720/JHIT.54012022.8.
[43] D. M. W. Powers, "Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation," no. January 2011, 2020, doi: 10.9735/2229-3981.
[44] S. Sathyanarayanan, "Confusion Matrix-Based Performance Evaluation Metrics," African J. Biomed. Res., no. November, pp. 4023–4031, 2024, doi: 10.53555/ajbr.v27i4s.4345.