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Customer Clustering by Combining the Particle Swarm And K-Means Algorithms and Analyzing Their Behavior on Commercial Websites

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Abstract
One of the trends in modern management is the consideration of the principle of customer orientation and customer satisfaction. Following this approach, online shopping, as one of the goods and services distribution channels, is also inclined to maintain and expand relations with customers. Nonetheless, what has become even more highlighted in the competition arena is going beyond customer satisfaction by predicting the customers' behavior in order to properly respond to their needs and ultimately, establish loyalty. One of the methods used to know the customers is the clustering approach. Clustering is a data mining technique that takes a number of items and places them in clusters based on their attributes. One of the problems of the k-means clustering is that it has no specific method for primary determination or calculation of the cluster centers. Therefore, in order to optimize the clusters, we use the particle swarm optimization (PSO) algorithm. In the end, we analyze these clusters using the RFM model to analyze the customers' behavior. What is achieved by analysis of each cluster is finding the cluster of the most loyal customers. In this study, we specify the number of optimized clusters using the k-means clustering algorithm. Then, we use the obtained number of clusters for the primary adjustment in the particle swarm optimization algorithm. Finally, we score the achieved clusters by the RFM method so that we can identify the most loyal customers that are placed in the cluster with the highest score.

Keywords: Commercial Websites, Clustering, Customer Behavior Analysis, K-Means Clustering, Particle Swarm Optimization (PSO).

1. INTRODUCTION

Today, many methods are used for clustering. The importance of clustering in data analysis is so much that the results of this important task directly affect the realization

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of the data analysis purposes and achievement of a reliable result. Moreover, there are various clustering methods and algorithms that has developed, as k-means, Particle swarm optimization (PSO), Optimum-path forest (OPF) [1], [2]and etc. Therefore, choosing the appropriate method is of high importance. In this research, we tried several steps to achieve a reliable result for our data analysis. This study describes and analyzes the data using five steps which are detailed as follows. The first step presents the definitions for the customer behavior analysis purposes, the second step deals with preprocessing of the data, the third step includes clustering by the particle swarm optimization algorithm (PSO) and k-means, the fourth step provides the customer behavior analysis by RFM technique and ultimately, the simulation results are extracted in the fifth step.

Simulation has been performed by MATLAB software in this research.

Online Shopping: Online shopping has gained great popularity recently. That's due to the pandemic situation and probability of COVID-19 contagious. Despite an array of gains, it inflicts challenges[3]. Today, a variety of services and goods are available online, resulting in development of online businesses.

Digikala E-commerce Company: As one of the oldest online stores with more than a decade of experience, Digikala has managed to keep pace with the reputable stores of the world and become the largest online store of Iran by adhering to three key principles of onsite payment, 7-day return policy, and the guarantee of originality.

Big Data: Big Data refers to a set of unstructured data which have a very large volume, are obtained from varied resources such as the web, business organizations, etc. with different formats and are received by us at a high speed; thus, making their processing by ordinary database management tools complicated and exhausting [4].

Data Science: Data Science is a multidisciplinary science about extracting knowledge and awareness from a set of data and information. Data Science consists of a combination of various topics and is built upon the existing bases and methods in different scientific fields. Some of these fields include mathematics, statistics, data engineering, pattern recognition, etc. The purpose of this science is to extract concepts from data and develop data-based products [5].

Meta-Heuristic Algorithms: They are used to sort out problems in an impressive way. They develop reliable solutions than classic methods. In addition, a heuristic algorithm gives an expedient outcome for a particular scope of the problem [6]–[8].

K-means Algorithm: The k-means method is one of the data clustering methods used in data mining. In spite of its simplicity, this method is considered as a basic method for many other clustering methods. It is an exclusive and flat method. Various forms have been stated for this algorithm but all of them have a repeated procedure that tries to make estimations such as obtaining some points as the cluster centers and attributing each sample data to one cluster for a fixed number of clusters [9].

Particle Swarm Optimization Algorithm (PSO)[10]–[12]**:** It is a global minimization method that can be used to deal with problems whose answer is a point or surface in an n-dimensional space. In this space, some assumptions are made and an initial speed is allocated to them. Then, these particles move in the answer space and the achieved results are calculated based on a measure of quality after each time frame. With the passage of time, particles accelerate towards the particles with best fitness and aggregation of individual preference relations [13] in a similar relation group.

Customer Analysis: Customer analysis helps the big data become big values that enable the organizations to predict the buyers' behavior and consequently, improve their sales, market optimization, inventory planning, fraud identification and many other uses. A wide range of approaches are available and can be implemented [14].

RFM Analysis Model: This analysis model which is based on recency, frequency and monetary parameters have been a solution for the base of direct marketing distribution for decades [15], [16]. In this model, the customers' performance in purchase and amount of their purchase are studied based on their purchase continuance and it has been always been highly considered. This is the simplest customer classification model based on each of these variables in which by calculating the score given to them, we can identify the most loyal customers based on the higher score [17].

2. DESIGN PROCESS

2.1. Dataset Determination

As one of the oldest online stores with more than a decade of experience, Digikala has managed to keep pace with the reputable stores of the world and become the largest online store of Iran by adhering to three key principles of onsite payment, 7-day return policy, and the guarantee of originality.

In this study, the dataset of Digikala which has been presented by Noavaran Fan Avazeh Company (Digikala Online Store) is used. This dataset is introduced under the name "DK-Dataset 3" which is related to the customers' purchase history.

DK-Dataset 3 includes one hundred thousand purchase records of the customers which have become anonymous like other data of Digikala so that the customers' privacy is protected. These data have time and location. Among the uses of these data, analysis of trends among cities, customers' purchase and order prediction and customer classification can be mentioned. The order of fields in this dataset is as follows:

- ID_Order: Order No.
- ID_Customer: Customer No.
- ID_Item: Data Item No.
- DateTime_Cart Finalize: Purchase Time
- Amount_Gross_Order: Purchase Amount
- City_name_fa: Name of the City
- Quantity_item: Number of Data Items

Different versions of the Digikala dataset can be downloaded from the following link: https://www.digikala.com/landing/datamining

2.2. Data Processing

In the recommender systems, samples are usually indicated by vectors in a multidimensional space while each dimension of the intended space indicates a specific attribute (data item) of the samples. If it is assumed that we have n records (users) with d data items each, we can form an n by d matrix in which each row is a sample (record/user) and each column is a specific attribute (data item) related to the samples. This matrix can be called the polygonal data matrix which is developed on the dataset after the necessary processing. The aim of this preprocessing is to develop the matrix of user tastes and a dataset without the invalid data in this phase.

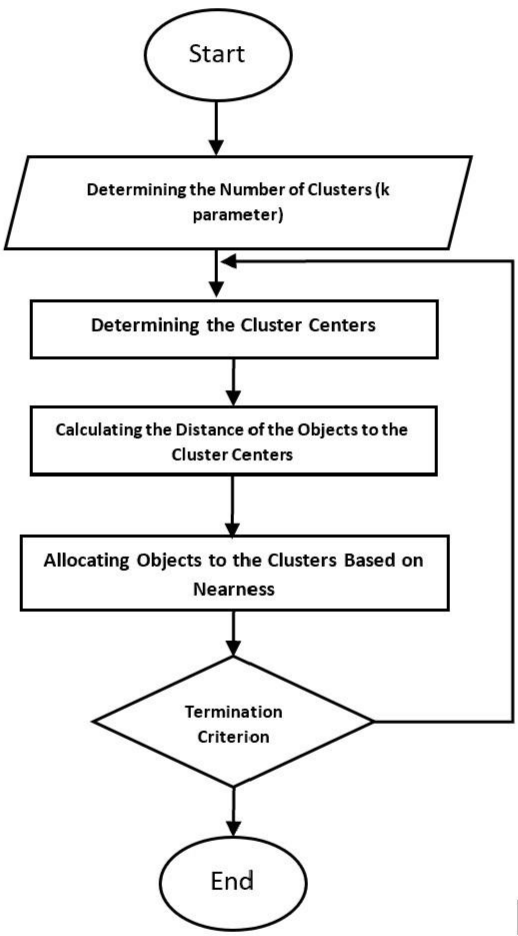

Fig. 1. K-means flowchart.

2.3. Calculation of the Optimal Number of Clusters by K-means

The k-means method is one of the data clustering methods used in data mining. In spite of its simplicity, it is considered a basic method for many other clusterings methods (such as fuzzy clustering).

K-means is considered an exclusive and flat method. Various forms have been stated for this algorithm but all of them have a repeated procedure which is performed for a fixed number of clusters: 1) Obtaining some points as the cluster centers. These points are in fact the mean points of each cluster; 2) Attributing each sample data to one cluster. These data should have the shortest distance to the center of this cluster. In a simple type of this method, some points are randomly chosen for the required number of clusters. Then, the data are attributed to one of these clusters based on the amount of nearness (similarity) and this way, new clusters are formed. By repeating this same procedure, new centers can be calculated by obtaining the mean of the data in each repetition and the data can be reattributed to new clusters.

This procedure will continue until no more change is made in the data. In the general state, the formula shall be as follows [11]:

$$E = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left\| x_{ij} - m_i \right\| \quad (1)$$

x_{ij} is the sample j of i-class, m_i is the center of i-class, n_i is the number of samples i-class

Input: N objects to be cluster $\{x_1, x_2 \ldots x_n\}$, the number of clusters k

Output: k clusters and the sum of dissimilarity between each object and its nearest cluster center is the smallest

Arbitrarily select k objects as initial cluster centers (m_1, m_2...m_k);

Calculate the distance between each object x_i and each cluster center, then assign each object to the nearest cluster, formula for calculating distance as:

$$d\left(x_i, m_i\right) = \sqrt{\sum_{j=1}^{d}\left(x_{i1} - m_{j1}\right)} \tag{2}$$

$i = 1,2...N_j = 1,2...k$ $d(x_i,m_j)$ is the distance between data i and cluster j;

Calculate the mean of objects in each cluster as the new cluster centers,

$$m_i = \frac{1}{N_i}\sum_{j=1}^{N_i} x_{ij} \tag{3}$$

i=l, 2 . . . k; Ni is the number of samples of current cluster i;

The flowchart of the stages for calculation of the k-means is given in Fig. 1.

2.4. User Clustering by Particle Swarm

In this phase, we cluster the customers using the particle swarm optimization algorithm [18],[19]. The flowchart related to the third phase is shown in Figure 2. Firstly, we define some terms and the issue of clustering. We have used the results achieved from this k-means clustering as an effective parameter in particle swarm clustering to achieve more optimal results [12].

A pattern is a physical or abstract structure of objects. These patterns are distinguished from each other by a set of specific attributes called a trait. These traits together indicate a pattern. Assume that P= {P_1, P_2...P_N} is a set of patterns or data points that have d traits each. In this case, the patterns can be illustrated by a data matrix $X_{(n\times d)}$ (it is known as the tastes matrix in the recommender systems) which has d-dimensional row vectors.

The vector of i^{th} row of X_i specifies the i^{th} object of the set P and $X_{i,j}$ in X_i corresponds to the i^{th} actual value of the trait (j= 1, 2, …, d) of the i^{th} pattern (i= 1, 2, …, n). Considering $X_{(n\times d)}$, a clustering algorithm tries to find a partition in the form of C= {C_1, C_2…C_3 } with k classes so that the similarity of the patterns in one cluster is maximum (minimum distance) and similarity of the patterns from different clusters is minimum (maximum distance). The clusters must have the following characteristics[20]:

Two different clusters should have a minimum one allocated pattern, i.e:

$$c_i \neq 0 \quad \forall i \in \{1, 2...k\} \tag{4}$$

Two different clusters should have no common patterns. This characteristic is needed for hard clustering but it is not needed in fuzzy clustering.

$$c_i \cap c_j = 0 \quad \forall i \neq j \ \text{ and } \ \mathrm{i.j} \in \{1, 2...k\} \tag{5}$$

Each pattern should be definitely allocated to one cluster.

$$\bigcup_{i=1}^{k} c_i = p \tag{6}$$

Since different datasets can be clustered by different methods that have all of the above characteristics, a fitness function should be defined for the partition. In this

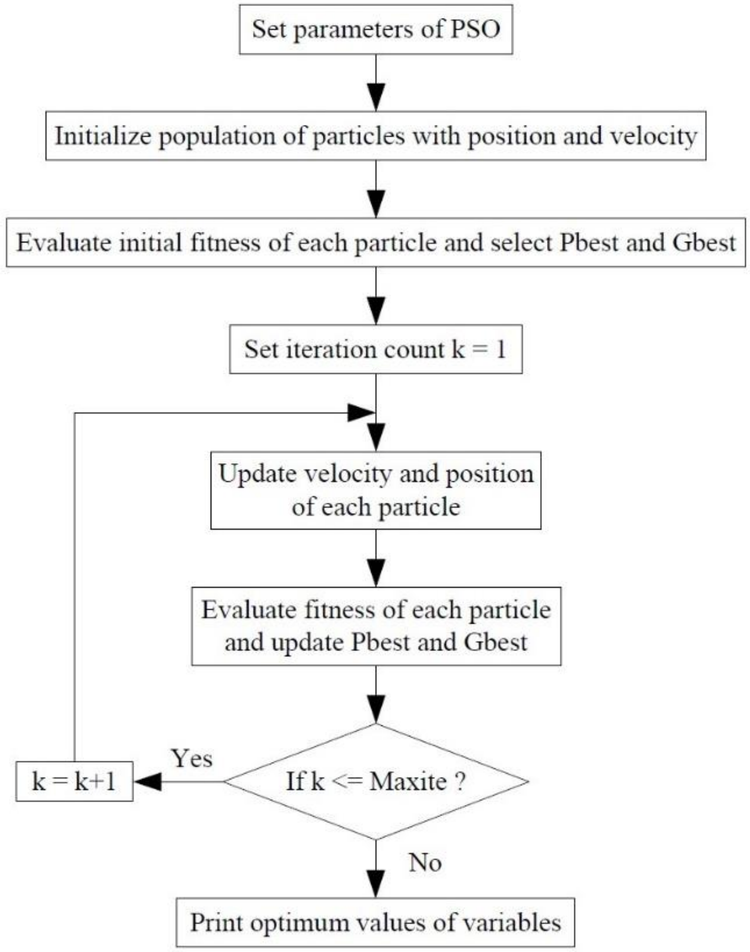

Fig. 2. Flowchart of PSO.

case, a partition like C* should be found that is optimal or near optimal in comparison to all other solutions.

$$c = \left\{ c^1, c^2 \ldots c^{N(n.k)} \right\} \tag{7}$$

where N (n.K) is defined as the following relation and indicates the number of the possible partitions.

$$N(n.k) = \frac{1}{K!} \sum_{i=1}^{K} -1^i \binom{K}{j}^i (K-i)^i \tag{8}$$

In other words, it can be written as the following relation:

$$optimize_{c}^{f(X_{n\times d}.C)} \tag{9}$$

In the (9) relation, C is a single partition of the **c** and **f** set which is a statistical mathematical function that indicates the quality of a partition based on measurement of the similarity between the patterns. Defining a proper similarity criterion plays a fundamental role in data clustering. The most common method for measuring the similarity between the patterns is using the distance criterion. The Euclidean distance is widely used as the criterion for measuring the similarity between the patterns. This criterion calculates the distance between two d-dimensional patterns of X_i and X_j in the data set by the following relation:

$$d(X_i.X_j) = \sqrt{\sum_{P=1}^{d}\left(X_{i.p} - X_{j.p}\right)^2} = \left\|X_i - X_j\right\| \tag{10}$$

In the clustering based on PSO, the fitness function is measured by the quantity error in order to study the clustering performance. Each particle in the PSO algorithm is indicated in the form of a possible set of k cluster centers. Besides, the quality of each particle is measured by the fitness function. In addition, relations (11) and (12) calculate the minimum Euclidean distance between a pair of clusters.

$$\begin{aligned} &\bar{d}_{\max} = \max\left\{\sum d\left(X_p.V_{i.k}\right)/n_{i.k}\right\} \\ &k \in 1,2...K \\ &\forall X_p \in C_{i.k} \end{aligned} \tag{11}$$

$$\begin{aligned} &d_{\min}(Z_i) = \min\left\{d\left(V_{i.p}.V_{i.q}\right)\right\} \\ &\forall p.q \;\; p \neq q \end{aligned} \tag{12}$$

In the (11) and (12) relations, $n_{i.k}$ is the number of patterns belonging to the $C_{i.k}$ cluster of the i^{th} particle. The fitness function is also a multi-objective optimization problem that minimizes the intra-cluster distances, maximizes the inter-cluster distances and reduces the quantity error. The flowchart of the stages is given in the Fig. 2.

2.5. Cluster Analysis by RFM

Customer clustering alone has no usable results for e-commerce companies [21]–[26]. Therefore, proper analyses should be carried out after clustering. In this study, RFM model is used for the analysis of output clusters in the suggested approach. This technique presents a multidimensional view towards customer behavior analysis for companies. So, we have placed the customers with the same taste in one group by clustering the customers. Now, by scoring them based on the RFM parameter, we can choose the most loyal cluster. The steps taken in this analysis are as follows:

We calculate the values of each RFM parameter for each customer.

We obtain the values of RFM parameters for each cluster based on the mean of each parameter.

We obtain the RFM score for each cluster by multiplication of the parameters.

We compare the obtained values to determine the most loyal cluster.

2.6. Study of Results Achieved from Cluster

In this section, we obtain the most loyal cluster by analyzing the RFM values of each cluster. The most cluster will be the cluster that has achieved the highest RFM in scoring.

3. IMPLEMENTATION PROCESS

3.1. Adjustment of Parameters

The suggested algorithm that has been recommended based on the references [27], [28] is used for setting initial values (Table-1) . It is noteworthy that the number of repetitions has been obtained based on the analysis in implementation which will be explained of the clustering dimension according to the three-dimensional model and centroids based on the output of the calculations of the k-means algorithm.

3.2. Preprocessing of the Dataset

The output of this phase is the preprocessed data that allows knowledge extraction in the subsequent phases. Furthermore, the operations carried out in this phase will solve different issues of the data of the studied problem. Therefore, the data are refined and prepared for performing the clustering phases. These operations can include data cleansing, dimension reduction and sampling. One of the common issues of the data is its low quality. Cleansing refers to the operations that result in removing the problem of data quality.

Thus, the lost data are determined by the average method in this section because some values of the dataset fields might be NULL for various reasons.

Table 1. ***Initial values.***

Variable	Description	Value
$c1$	Individual Learning Ratio	1.49
$c2$	Global Learning Ratio	1.49
w	Inertia Ratio	0.72
iteration	Clustering Dimension	20
dimension	Repetition	3
centroid	Centroids	6

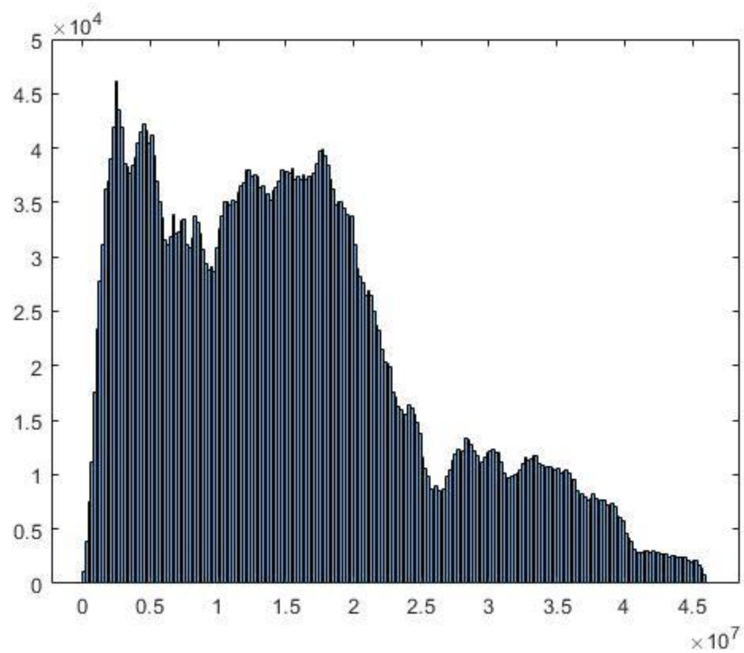

Fig. 3. Distance histogram.

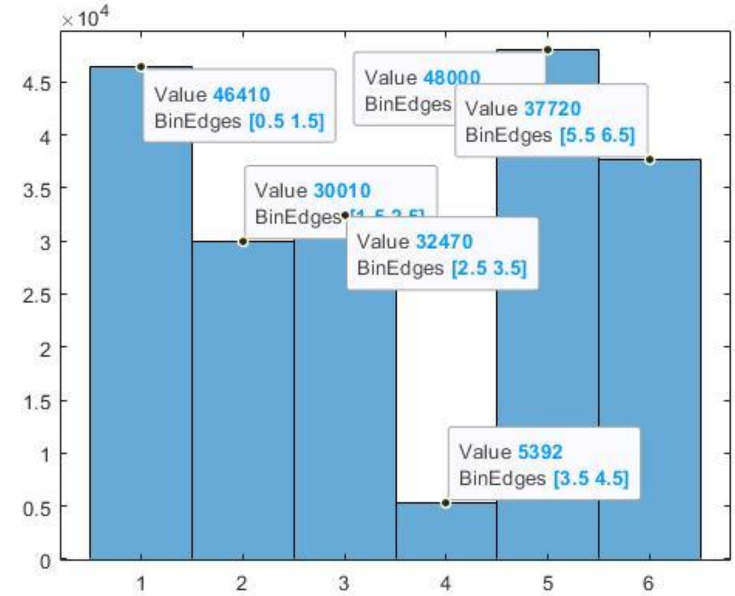

Fig. 4. Entities number of clusters.

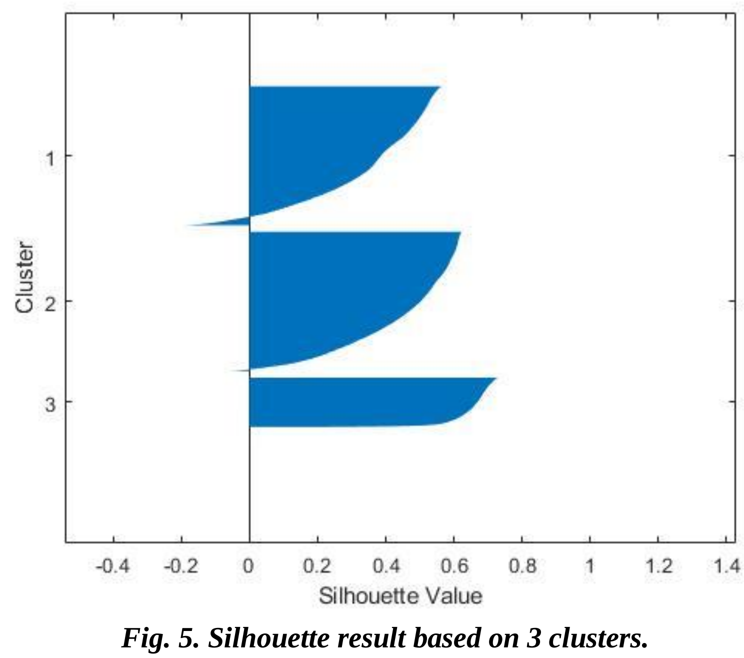

Fig. 5. Silhouette result based on 3 clusters.

3.3. Results of Clustering by K-means Algorithm

In this section, clustering of the customers using the k-means algorithm has been carried out in MATLAB. The distance histogram is illustrated in Figure 3.

Based on implementation of the algorithm, the number of entities in each cluster which has been presented in Figure.4.

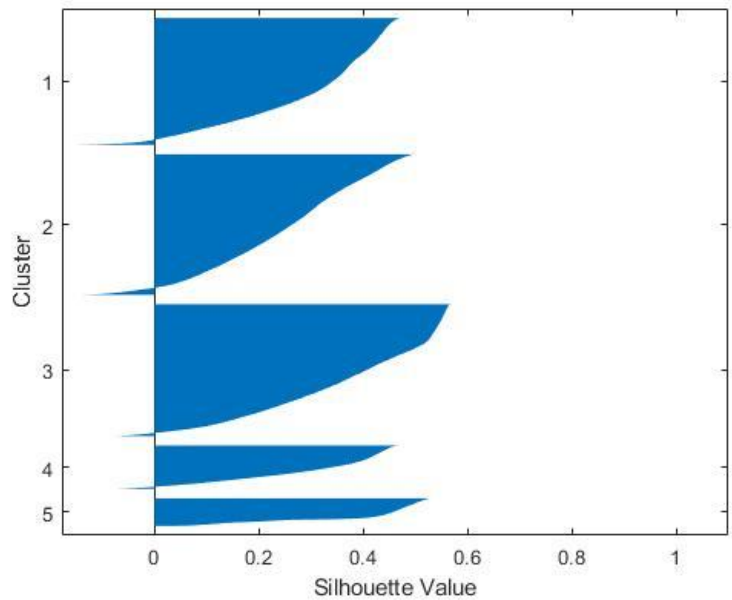

Fig. 6. Silhouette result based on 5 clusters.

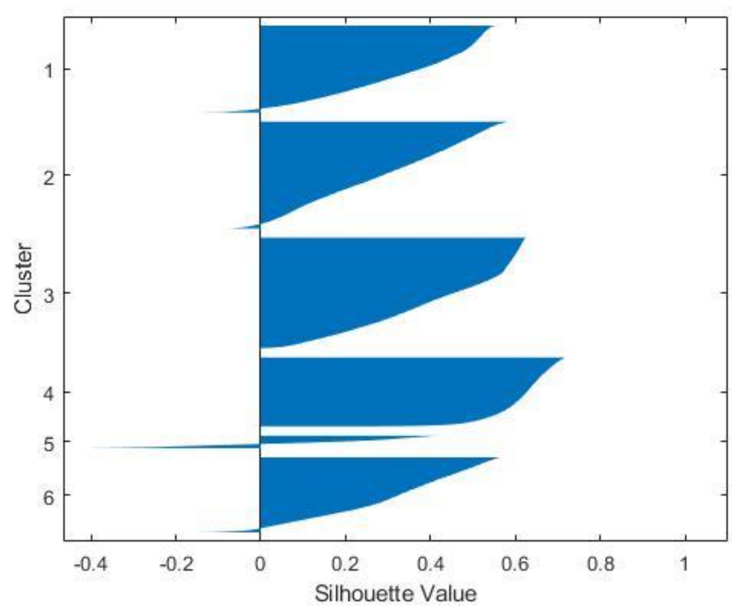

Fig. 7. Silhouette result based on 6 clusters.

Considering the achieved results and in order to ensure that the number of clusters is optimal, we use Silhouette algorithm. In this algorithm, according to the obtained graphs, the best state is when the graph shapes are closer to 1. To study different states (Figures 5-8), we put 3, 5, 6 and 7 for the number of clusters as the numerical parameter and we study the results achieved from the drawn graphs.

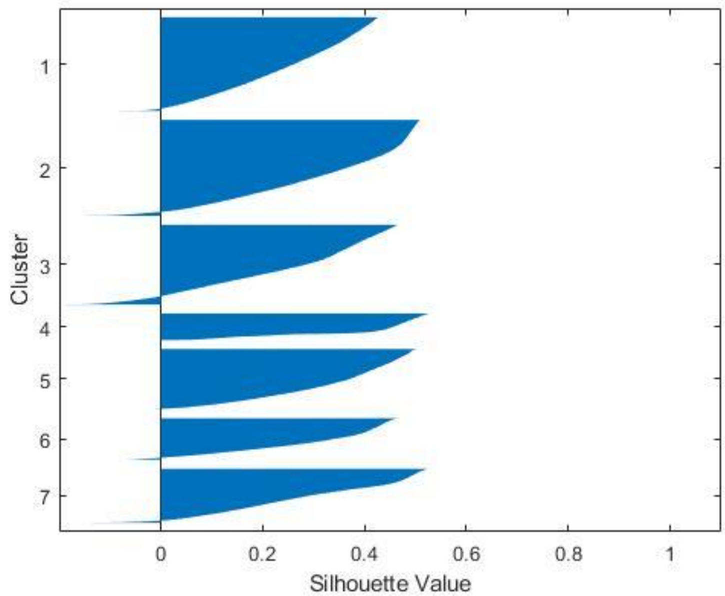

Fig. 8. Silhouette result based on 7 clusters.

Table 2. ***Relation between iteration and best fitness.***

Item	Iteration	Best Fitness
1	10	500
2	20	355
3	30	895
4	40	980

As you can see in Figure 7, 6 clusters have the best state compared to others. Therefore, we use this number as the parameter for the initial adjustment in the next phase.

3.4. Results of Clustering by Particle Swarm Algorithm

Therefore, the results achieved from running the algorithm with the different number of repetitions are presented. The algorithm was run for 10 to 100 repetitions so that the best result for the number of repetitions in the algorithm is determined. Based on the results, the algorithm has optimal performance when the target function is minimized.

The initial values for adjustment of the particle swarm algorithm are as follows:

centroids = 6; Result of K-means

dimensions = 3; how many dimensions in each centroid

particles = 6; how many particles in the swarm, how many solutions

iterations = 20; % iterations of the optimization algorithm

Considering the value of the number of clusters that has been obtained in the previous phase, this value is put in the variable particles.

Furthermore, for implementation, the number of repetitions has been taken as 20 and certain values were put in the program code. Ultimately, based on the values of best fitness, the iteration value with the best result was used (Table 2).

3.5. Behavior Analysis by RFM

In order to evaluate RFM, many ways are presented in various articles while the most common way is to calculate the value by multiplying all three values. In some instances, multiplication by weighing is also recommended [29]. We used multiplication without weighting in this implementation and Table 3 has been achieved by this method.

Considering Table 3 and the score of each cluster we can determine the value of each cluster and specify the best cluster in terms of the most loyal customers Table 4.

The numbers in the Rate column indicate each cluster's rank. Therefore, cluster 1 with 8258 customers is known as the best cluster which means that our most loyal customers are in this cluster.

Table 3. ***RFM clusters score*.**

	R	F	M	RFM Score
Cluster 1	0.747981	1.137564	450992	383687.2
Cluster 2	0.142857	1.120812	1146246	183532.3
Cluster 3	0.142857	1.037786	1529597	226770.5
Cluster 4	0.143228	1.108255	1250187	198445.9
Cluster 5	0.142857	1.028479	1470849	216105.4
Cluster 6	0.142857	1.05016	1651676	247789.2

Table 4. ***Clusters rating***

	# of Users	RFM Score	Rate
Cluster 1	8258	383687.2	1
Cluster 2	10537	183532.3	6
Cluster 3	11380	226770.5	3
Cluster 4	8092	198445.9	5
Cluster 5	11482	216105.4	4
Cluster 6	11244	247789.2	2

4. CONCLUSION

Using the intended approach, we basically managed to identify the most loyal group of our customers by combining clustering and customer behavior analysis through RFM. This loyal group has been obtained using the k-means clustering and PSO. Taking advantage of this model, we classified the customers with similar tastes in the same group.

The combination of the two clustering algorithms has given us clusters with more optimal members. Therefore, the achieved results are more favorable results for us. These results will be highly efficient and effective for business campaigns in terms of marketing opportunities.

REFERENCES

[1] H. Bostani, M. Sheikhan, and B. Mahboobi, "A Strong Coreset Algorithm to Accelerate OPF as a Graph-based Machine Learning in Large-Scale Problems," *Inf. Sci.*, p. S0020025520309968, Oct. 2020, doi: 10.1016/j.ins.2020.10.009.

[2] H. Bostani, M. Sheikhan, and B. Mahboobi, "Developing a fast supervised optimum-path forest based on coreset," in *2017 Artificial Intelligence and Signal Processing Conference (AISP)*, Shiraz, Oct. 2017, pp. 172–177, doi: 10.1109/AISP.2017.8324076.

[3] B. Tarhini and D. Hayek, "The Effect of Proper Complaint Handling on Customers' Satisfaction and Loyalty in Online Shopping," in *Business Revolution in a Digital Era*, A. M. Dima and F. D'Ascenzo, Eds. Cham: Springer International Publishing, 2021, pp. 405–421.

[4] I. Bobriakov, "Top 10 Data Science Use Cases in Retail," *ActiveWizards: machine learning company*, Jul. 22, 2018.

[5] W. van der Aalst, "Data Science in Action," in *Process Mining*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2016, pp. 3–23.

[6] A. Pradhan, S. K. Bisoy, and A. Das, "A Survey on PSO Based Meta-Heuristic Scheduling Mechanism in Cloud Computing Environment," *J. King Saud Univ. - Comput. Inf. Sci.*, p. S1319157821000033, Jan. 2021, doi: 10.1016/j.jksuci.2021.01.003.

[7] "Heuristic," *Wikipedia*. Jan. 02, 2021, Accessed: Jan. 21, 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Heuristic&oldid=997870792.

[8] L. Abualigah *et al.*, "Advances in Meta-Heuristic Optimization Algorithms in Big Data Text Clustering," *Electronics*, vol. 10, no. 2, p. 101, Jan. 2021, doi: 10.3390/electronics10020101.

[9] J. Zhu and H. Wang, "An improved K-means clustering algorithm," in *2010 2nd IEEE International Conference on Information Management and Engineering*, Chengdu, China, 2010, pp. 190–192, doi: 10.1109/ICIME.2010.5478087.

[10] S. Molaei, H. Moazen, S. Najjar-Ghabel, and L. Farzinvash, "Particle swarm optimization with an enhanced learning strategy and crossover operator," *Knowl.-Based Syst.*, vol.

215, p. 106768, Mar. 2021, doi: 10.1016/j.knosys.2021.106768.

[11] P. Vora and B. Oza, “A Survey on K-mean Clustering and Particle Swarm Optimization,” vol. 1, no. 3, p. 3, 2013.

[12] A. L. Ballardini, “A tutorial on Particle Swarm Optimization Clustering,” *ArXiv180901942 Cs*, Sep. 2018, Accessed: Jan. 01, 2020. [Online]. Available: http://arxiv.org/abs/1809.01942.

[13] F. Liu, J. Zhang, and T. Liu, “A PSO-algorithm-based consensus model with the application to large-scale group decision-making,” *Complex Intell. Syst.*, vol. 6, no. 2, pp. 287–298, Jul. 2020, doi: 10.1007/s40747-020-00144-5.

[14] N. Jafari Momtaz, S. Alizadeh, and M. Sharif Vaghefi, “A new model for assessment fast food customer behavior case study: An Iranian fast-food restaurant,” *Br. Food J.*, vol. 115, no. 4, pp. 601–613, Apr. 2013, doi: 10.1108/00070701311317874.

[15] [L. Zhang, J. Priestley, J. DeMaio, S. Ni, and X. Tian, “Measuring Customer Similarity and Identifying Cross-Selling Products by Community Detection,” *Big Data*, p. big.2020.0044, Dec. 2020, doi: 10.1089/big.2020.0044.

[16] O. Emam, A. Taher, and H. Fahmy, “Customer Analysis Model for Trusted Online Merchant,” *Commun. Appl. Electron.*, vol. 7, no. 34, pp. 18–24, Oct. 2020, doi: 10.5120/cae2020652872.

[17] Y. Zhang, E. T. Bradlow, and D. S. Small, “Predicting Customer Value Using Clumpiness: From RFM to RFMC,” *Mark. Sci.*, vol. 34, no. 2, pp. 195–208, Mar. 2015, doi: 10.1287/mksc.2014.0873.

[18] M. N. Alam, “Particle Swarm Optimization: Algorithm and its Codes in MATLAB,” p. 10.

[19] M. N. Alam, B. Das, and V. Pant, “A comparative study of metaheuristic optimization approaches for directional overcurrent relays coordination,” *Electr. Power Syst. Res.*, vol. 128, pp. 39–52, Nov. 2015, doi: 10.1016/j.epsr.2015.06.018.

[20] A. A. A. Esmin, R. A. Coelho, and S. Matwin, “A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data,” *Artif. Intell. Rev.*, vol. 44, no. 1, pp. 23–45, Jun. 2015.

[21] I. Maryani and D. Riana, “Clustering and profiling of customers using RFM for customer relationship management recommendations,” in *2017 5th International Conference on Cyber and IT Service Management (CITSM)*, 2017, pp. 1–6.

[22] R. A. Daoud, A. Amine, B. Bouikhalene, and R. Lbibb, “Combining RFM model and clustering techniques for customer value analysis of a company selling online,” in *2015 IEEE/ACS 12th International Conference of Computer Systems and Applications (AICCSA)*, 2015, pp. 1–6.

[23] R. Qiasi, M. Baqeri-Dehnavi, B. Minaei-Bidgoli, and G. Amooee, “Developing a model for measuring customer’s loyalty and value with RFM technique and clustering algorithms,” *J.*

Math. Comput. Sci., vol. 4, no. 2, pp. 172–181, 2012.

[24] R. Valarmathi and T. Sheela, “RFM-PSO -RFM Score based PSO Task Scheduling in Cloud,” vol. 8, no. 6, p. 5, 2019.

[25] [G. Sun *et al.*, “Using improved RFM model to classify consumer in big data environment,” *Int. J. Embed. Syst.*, vol. 14, no. 1, p. 54, 2021, doi: 10.1504/IJES.2021.111976.

[26] S. Hartini, W. Gata, S. Kurniawan, H. Setiawan, and K. Novel, “Cosmetics Customer Segmentation and Profile in Indonesia Using Clustering and Classification Algorithm,” *J. Phys. Conf. Ser.*, vol. 1641, p. 012001, Nov. 2020, doi: 10.1088/1742-6596/1641/1/012001.

[27] D. W. van der Merwe and A. P. Engelbrecht, “Data clustering using particle swarm optimization,” in *The 2003 Congress on Evolutionary Computation, 2003. CEC ’03.*, Canberra, ACT, Australia, 2003, pp. 215–220, doi: 10.1109/CEC.2003.1299577.

[28] F. Van Den Bergh, “An analysis of particle swarm optimizers,” phd, University of Pretoria, ZAF, 2002.

[29] C.-H. Cheng and Y.-S. Chen, “Classifying the segmentation of customer value via RFM model and RS theory,” *Expert Syst. Appl.*, vol. 36, no. 3, pp. 4176–4184, Apr. 2009, doi: 10.1016/j.eswa.2008.04.003.