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# Application of Fuzzy C-Means Algorithm for Clustering Fast Moving and Slow Moving Printing Materials at Satria Print MSME

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**ABSTRACT**

Inventory decisions in micro, small, and medium enterprises (MSMEs) are often based on experience rather than on systematic analysis of transaction records. This study applies the Fuzzy C-Means (FCM) algorithm to classify printing materials at Satria Print MSME into Fast Moving and Slow Moving groups. Fifty material records from January to March 2026 were described by sales quantity, transaction frequency, and final stock. After Min–Max normalization, FCM was run with two clusters, a fuzziness exponent of 2, and a stopping tolerance of 0.0001, and each material was assigned to the cluster with its largest membership degree. The algorithm converged after 11 iterations. Seventeen materials (34%) were classified as Fast Moving and 33 (66%) as Slow Moving. The strongest Fast Moving memberships were found for F4 70 gsm HVS paper (0.919), 150 gsm art paper (0.906), A4 thermal laminating film (0.886), and Epson yellow ink (0.859), indicating that core paper, laminating, and ink supplies deserve priority in stock monitoring. Because the variables were strongly correlated and final stock is not an unambiguous indicator of movement, the result is a first-stage segmentation that complements turnover-based analysis. Future studies should validate the number of clusters and use longer, multi-business datasets.

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## 1. INTRODUCTION

Information technology has changed the way business organizations collect, process, and use operational data. Data that were previously maintained primarily as transaction records can be transformed into information for managerial decision-making. Data mining provides analytical techniques for discovering useful patterns from collected data and has been applied to classification, association, prediction, and clustering problems

[1]. Clustering, in particular, groups observations so that objects in the same group are more similar to each other than to objects in other groups [2], [3].

Inventory management is one operational area that benefits from systematic data analysis. An imbalance between stock availability and material usage can cause shortages of materials needed for production or accumulation of items with low movement. Inventory items are therefore commonly classified by criteria such as usage value, lead time, and usage frequency, as in multiple-criteria ABC analysis [4], and items with infrequent demand require different forecasting and stocking rules from regularly demanded items [5]. Clustering of inventory records has been used to separate items with rapid and slow usage so that supply planning can focus on the most active items [6], [7], while conventional FSN (Fast, Slow, Non-moving) analysis classifies items by usage frequency or turnover ratio [8]. In printing businesses, the problem is particularly relevant because production depends on different types of paper, ink, laminating materials, and other supplies whose demand varies with customer orders.

Satria Print is a Micro, Small, and Medium Enterprise (MSME) engaged in invitation printing, stickers, banners, photo printing, document printing, and photocopying. The business uses various printing materials with different usage levels. Inventory recording is still conducted in a simple manner and has not been supported by structured analysis of material movement. Consequently, the owner may have difficulty identifying materials that should receive higher procurement priority. The problem becomes more visible before Eid al-Fitr, when invitation-printing orders may reach approximately 7,000 sheets per week according to the business owner.

Fuzzy C-Means (FCM), introduced by Dunn [9] and generalized by Bezdek [10], [11], is a clustering method in which each observation belongs to every cluster with a membership degree between 0 and 1. FCM has been applied to stock clustering and portfolio analysis [12], electronic-product sales [13], public-welfare data [14], customer grouping [15], and warehouse operations [16]. These studies indicate that FCM is useful when observations may belong partly to more than one group. However, they do not address the classification of printing materials at an MSME printing business using sales quantity, transaction frequency, and final stock simultaneously.

The specific research gap addressed in this study is therefore the limited empirical application of FCM to printing-material inventory management at the MSME level. Existing applications demonstrate the use of FCM in other objects and domains, but they provide limited evidence regarding how the method can be used to distinguish Fast Moving and Slow Moving printing materials in a real printing-business inventory context.

The novelty of this study lies in applying FCM to 50 printing-material records from Satria Print MSME using three operational variables—sales quantity, transaction frequency, and final stock—to produce two movement categories. The combination is intended to represent both demand-side activity and the stock position of materials. The study also translates the resulting clusters into practical inventory-management implications for procurement and warehouse control.

Accordingly, this study aims to apply the FCM algorithm to cluster printing materials at Satria Print MSME into Fast Moving and Slow Moving categories. The

specific objective is to determine the resulting cluster composition and identify materials with strong membership in the Fast Moving cluster. The contribution of the study is practical: the resulting classification can provide an additional data-based reference for procurement prioritization, stock monitoring, and warehouse-space management.

## 2. METHOD

This study used a quantitative descriptive research design. The quantitative approach was selected because the analysis uses numerical transaction and inventory variables, while the descriptive approach was used to describe the resulting material clusters. The FCM algorithm was selected as the main data-analysis technique because it assigns membership degrees to clusters rather than forcing each observation into a single hard cluster [10]. The study proceeded through data collection, data checking and variable selection, Min–Max normalization, FCM clustering, and interpretation of the final clusters (Figure 1).

### 2.1. Research Location, Time, Population, and Sample

The research was conducted at Satria Print MSME using transaction and inventory records for the period January 2026 to March 2026. This period includes the weeks before Eid al-Fitr, when invitation orders peak. The population consisted of the printing-material records available in the study period, and all 50 eligible records were analyzed (census); no sampling was performed.

### 2.2. Data Sources and Data Collection

The study used primary contextual information and secondary operational records. Observation was conducted to understand the inventory-recording process; interviews with the business owner were used to obtain information about procurement practices and inventory-management problems; and documentation was used to collect sales quantity, transaction frequency, and final-stock records. The data-collection instruments were an observation guide, an interview guide, and a documentation format for recording the required transaction variables. The owner indicated that procurement decisions had previously relied substantially on experience and estimation, while the transaction records had not been systematically analyzed.

### 2.3. Variables and Data Preparation

Three variables were used in the clustering analysis: sales quantity ($X_1$), transaction frequency ($X_2$), and final stock ($X_3$). Sales quantity is the quantity of material sold or used during the study period, expressed in the recording unit of each material (e.g., sheets, rolls, or bottles); transaction frequency is the number of transactions involving the material; and final stock is the quantity remaining at the end of the observation period. Because the three variables have different numerical scales, each variable was transformed to the interval [0, 1] with Min–Max normalization before clustering [1]; range-based standardization of this kind has been shown to preserve cluster structure better than other standardization procedures [17]:

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$$x'_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (1)$$

where $x_{ij}$ is the value of variable j for material i (i = 1, 2, …, n; j = 1, 2, …, p), $x'_{ij}$ is its normalized value, n = 50 is the number of materials, and p = 3 is the number of variables.

### 2.4. Data Quality and Analysis Technique

Data quality was checked by comparing the documented records with the inventory and transaction information obtained from the business during data collection. Because the dataset consisted of operational records rather than a questionnaire administered to human respondents, questionnaire validity and reliability testing were not applicable. The analysis consisted of Min–Max normalization followed by FCM clustering. No personal customer data were included in the analytical variables.

### 2.5. Fuzzy C-Means Algorithm

FCM partitions the n normalized observations into c clusters by minimizing the weighted within-cluster objective function [10], [11]:

$$J_m(U,V) = \Sigma_{i=1}^{n} \Sigma_{k=1}^{c} (\mu_{ik})^m d_{ik}^2 \quad (2)$$

where $U = [\mu_{ik}]$ is the membership matrix, $V = [v_{kj}]$ is the matrix of cluster centers, $\mu_{ik}$ is the membership degree of material i in cluster k (k = 1, 2, …, c), $d_{ik}$ is the distance between material i and the center of cluster k, and m > 1 is the fuzziness exponent. The minimization is carried out iteratively through the steps below.

#### 2.5.1. Initialize Parameters

The analysis used two clusters (c = 2), a fuzziness exponent m = 2, which is the most common choice and lies within the range 1.5–2.5 recommended for FCM [18], a stopping tolerance ε = 0.0001, and a maximum of 100 iterations. The iterative process started from an initial membership matrix, which was updated in every iteration.

Each row of the membership matrix must satisfy:

$$\Sigma_{k=1}^{c} \mu_{ik} = 1, \qquad 0 \le \mu_{ik} \le 1, \qquad i = 1,2,\ldots,n \quad (3)$$

The membership values are then updated in every iteration until the convergence criterion is satisfied.

#### 2.5.2. Calculate Cluster Centers (Centroids)

Given the membership matrix, the center of each cluster is calculated as [10]:

$$v_{kj} = \frac{\sum_{i=1}^{n}(\mu_{ik})^{m} x'_{ij}}{\sum_{i=1}^{n}(\mu_{ik})^{m}} \quad (4)$$

### 2.5.3. Calculate Distance to Cluster Centers

The distance between each material and each cluster center is calculated using the Euclidean distance:

$$d_{ik} = \sqrt{\sum_{j=1}^{p}(x'_{ij} - v_{kj})^{2}} \quad (5)$$

where p = 3 is the number of variables.

### 2.5.4. Update Membership Degrees

Membership degrees are updated as [10]:

$$\mu_{ik} = \frac{1}{\sum_{l=1}^{c}\left(\frac{d_{ik}}{d_{il}}\right)^{2/(m-1)}} \quad (6)$$

### 2.5.5. Convergence Check

The iteration stops when the error value, defined as the change between two successive iterations, falls below a or when the maximum number of iterations is reached. After convergence, each material was assigned to the cluster with its largest membership degree, and the two clusters were labeled Fast Moving and Slow Moving by comparing the characteristics of the materials in each cluster.

## 2.6. Research Procedure

The research procedure, from data collection to the interpretation of the final clusters, is summarized in Figure 1.

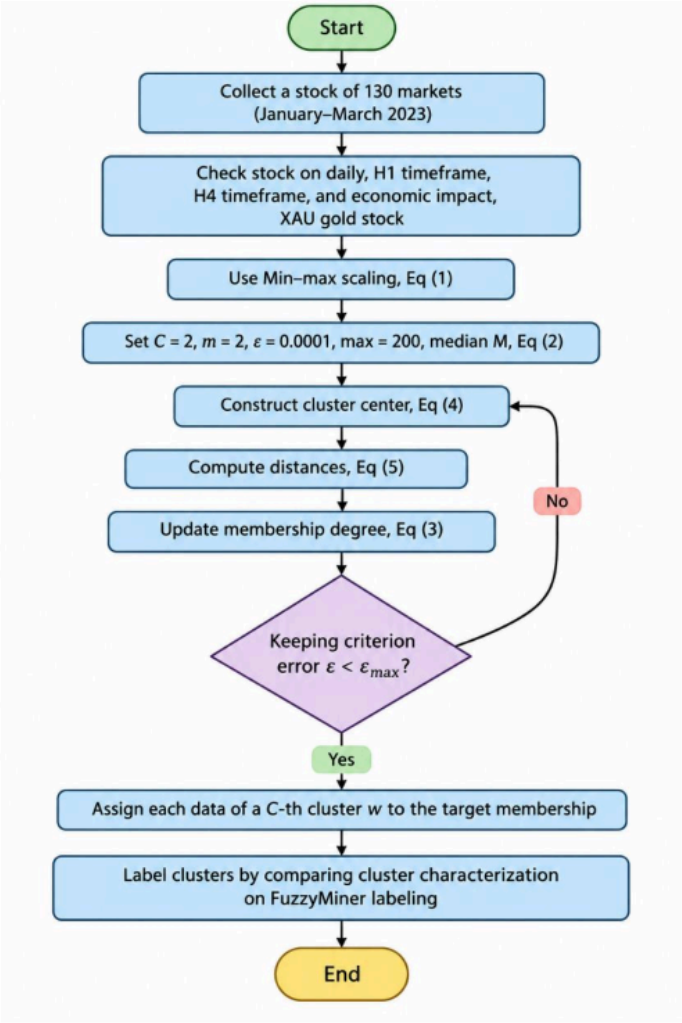



Figure 1. Research procedure and FCM steps

## 3. RESULTS AND DISCUSSION

This section presents the results for the 50 printing-material records: the descriptive characteristics of the variables and their normalization, the convergence of FCM, the final cluster composition, and the materials with the strongest membership in the Fast Moving cluster.

### 3.1. Results

#### 3.1.1. Descriptive Characteristics and Normalization

Table 1. Minimum and maximum values of the variables (n = 50)

| Variable | Minimum | Maximum |
|---|---|---|
| Sales quantity ($X_1$) | 121 | 12,100 |
| Transaction frequency ($X_2$) | 5 | 50 |
| Final stock ($X_3$) | 10 | 17,579 |

Table 2. Normalized values of the first ten records (BHN001–BHN010)

| Material Code | $X_1$ norm | $X_2$ norm | $X_3$ norm |
|---|---|---|---|
| BHN001 | 0.0826 | 0.4000 | 0.1836 |
| BHN002 | 0.0557 | 0.3111 | 0.1068 |
| BHN003 | 0.1021 | 0.4444 | 0.2133 |
| BHN004 | 0.0367 | 0.2444 | 0.0682 |
| BHN005 | 0.1278 | 0.5111 | 0.2497 |
| BHN006 | 0.0193 | 0.2000 | 0.0364 |
| BHN007 | 0.1544 | 0.5778 | 0.2897 |
| BHN008 | 0.0096 | 0.1556 | 0.0168 |
| BHN009 | 0.1821 | 0.6444 | 0.3321 |
| BHN010 | 0.0038 | 0.1111 | 0.0064 |

The original variables have substantially different scales: sales quantity ranges from 121 to 12,100, transaction frequency from 5 to 50, and final stock from 10 to 17,579 (Table 1). Min–Max normalization places all variables on a common 0–1 scale, so that no variable dominates the Euclidean distance because of its unit [1]. In the ten records shown in Table 2, the three normalized variables are almost perfectly correlated (Pearson r = 0.995–0.997): materials with high sales quantity also have high transaction frequency and high final stock.

### 3.1.2. FCM Analytical Results

FCM was run with c = 2, m = 2, a maximum of 100 iterations, and ε = 0.0001. The process converged at the 11th iteration with an error value of 0.00009522, below the specified tolerance (Table 3).

Table 3. Error value per iteration

| Iteration | Error Value | Status |
|---|---|---|
| 1 | 0.23456120 | Continue |
| 2 | 0.08723410 | Continue |
| 3 | 0.03214560 | Continue |
| 4 | 0.01287630 | Continue |
| 5 | 0.00543210 | Continue |
| 6 | 0.00234560 | Continue |
| 7 | 0.00102340 | Continue |
| 8 | 0.00045620 | Continue |
| 9 | 0.00021340 | Continue |
| 10 | 0.00012450 | Continue |
| 11 | 0.00009522 | Converged |

The error value decreased from 0.23456120 at the first iteration to 0.00009522 at the 11th iteration, showing that the iterative solution stabilized under the specified stopping criterion. Convergence indicates only that the numerical procedure reached a stable partition; it is not a measure of cluster quality.

### 3.1.3. Final Cluster Composition

After convergence, the 50 records were assigned to the cluster with their largest membership degree, giving the two groups summarized in Table 4.

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Table 4. Final cluster composition

| Cluster | Category | Number of Materials | Percentage |
|---|---|---|---|
| C1 | Fast Moving | 17 | 34% |
| C2 | Slow Moving | 33 | 66% |

Seventeen records (34%) were classified as Fast Moving and 33 (66%) as Slow Moving. The larger Slow Moving group indicates that, in this dataset and period, most materials had movement characteristics closer to the Slow Moving cluster. This result describes the observed dataset and should not be generalized to other printing businesses without additional evidence.

### 3.1.4. Materials with Strong Fast Moving Membership

Table 5. Materials with the highest membership in the Fast Moving cluster

| Material Code | Material name (original name) | Membership C1 | Membership C2 |
|---|---|---|---|
| BHN021 | F4 HVS paper, 70 gsm (Kertas HVS F4 70gsm) | 0.9193 | 0.0807 |
| BHN033 | Art paper, 150 gsm (Kertas Art Paper 150gsm) | 0.9059 | 0.0941 |
| BHN045 | A4 thermal laminating film (Laminasi Thermal A4) | 0.8859 | 0.1141 |
| BHN018 | Epson yellow ink (Tinta Epson Yellow) | 0.8594 | 0.1406 |
| BHN007 | A4 paper, 80 gsm (Kertas A4 80gsm) | 0.8321 | 0.1679 |

Table 5 lists the five materials with the highest membership in Cluster C1. F4 70 gsm HVS paper has the highest membership (0.9193), followed by 150 gsm art paper (0.9059), A4 thermal laminating film (0.8859), Epson yellow ink (0.8594), and A4 80 gsm paper (0.8321). Because membership in FCM depends on the relative distances to both cluster centers, these values express how closely each material resembles the Fast Moving center rather than how large its sales are.

## 3.2. Discussion

The principal finding is that FCM separated the 50 printing-material records into two movement groups, with 17 records in Fast Moving and 33 in Slow Moving. The result shows how fuzzy clustering can represent different degrees of association with inventory-movement categories rather than relying only on a single rigid threshold. This characteristic is consistent with the conceptual basis of FCM, in which observations may have graded membership across clusters [10].

From a managerial perspective, the Fast Moving group can be used as an initial priority list for closer stock monitoring because these materials exhibit stronger association with the high-movement cluster. Procurement planning can use this information together with actual lead times, safety-stock policies, and current demand conditions rather than treating the cluster label as a stand-alone reorder rule.

The Slow Moving group can similarly be used to identify materials that warrant more cautious procurement and periodic review. However, a Slow Moving classification does not necessarily mean that a material is unimportant, because some low-frequency materials may still be required for specific customer orders, and such intermittent demand calls for its own forecasting and stocking rules [5]. Therefore, the clustering result should complement, rather than replace, managerial judgment and operational constraints.

The finding extends previous FCM applications in stock analysis, electronic-product sales, public-welfare data, customer grouping, and warehouse operations [12]–[16] by applying the method to printing-material inventory at an MSME. It is also consistent with inventory-clustering studies that separate items with rapid and slow usage to support supply planning [6]. Compared with FSN analysis, which assigns items to fixed classes from their usage frequency or turnover ratio [8], FCM provides graded memberships that can flag materials lying between the two groups. The contribution is contextual rather than a claim that FCM is superior to other clustering algorithms.

The convergence at iteration 11 shows that the stopping condition was met, but convergence alone does not establish that two clusters are the most appropriate partition. The number of clusters was fixed in advance; future work should evaluate it with fuzzy cluster-validity indices such as the partition coefficient [19], the Xie–Beni index [20], and related indices [18], [21], as well as with crisp criteria for the number of clusters [22] and the silhouette coefficient [23], [24].

The use of sales quantity, transaction frequency, and final stock combines demand-related and stock-position information, but two features of these variables limit their interpretation. First, final stock is not an unambiguous indicator of movement: a high final stock may reflect frequent replenishment of a fast-moving material or accumulation of a slow-moving one, which is why FSN analysis relies on turnover ratios [8]; inventory turnover, the ratio of sales to average inventory, is also the standard measure of how quickly inventory moves [25]. Second, in the sampled records the three variables are almost perfectly correlated (Section 3.1.1), so the clustering is driven mainly by the overall size of material activity. In addition, sales quantities are recorded in different units for different materials, which normalization does not remove. Using a turnover ratio and unit-free activity measures would make the movement classification more robust.

The practical implications of the findings are therefore focused on decision support. The resulting clusters can be used to support: (1) procurement prioritization, (2) warehouse-space review, (3) stock-out monitoring for frequently used materials, (4) periodic review of slow-moving items, and (5) data-based inventory discussions with the business owner.

The study has several limitations. The dataset covers one MSME and only the January–March 2026 period, which includes the pre-Eid peak, so the results may not represent other printing businesses or longer seasonal cycles. The number of clusters was fixed at two without cluster-validity indices, the clusters were labeled by comparing their characteristics rather than by reporting formal cluster centers, the FCM solution may depend on the initial membership matrix, and the results were not compared with FSN analysis, multiple-criteria ABC analysis [4], or other clustering methods [2]. The analysis

also does not include supplier lead time, purchase cost, or demand forecasts. These limitations should be considered when applying the classification to procurement decisions.

## 4. CONCLUSION

This study applied Fuzzy C-Means clustering to 50 printing-material records from Satria Print MSME to distinguish Fast Moving from Slow Moving materials using sales quantity, transaction frequency, and final stock. The algorithm classified 17 materials (34%) as Fast Moving and 33 (66%) as Slow Moving, with core paper, laminating, and ink supplies showing the strongest Fast Moving membership. This segmentation answers the research objective by giving the business a data-based reference for prioritizing procurement, monitoring stock-outs of frequently used materials, and reviewing slow-moving items periodically.

The findings should be interpreted as a first-stage segmentation rather than a definitive inventory policy. The analysis covers one business over three months that include the pre-Eid peak, the number of clusters was fixed in advance, and the variables were strongly correlated, with final stock acting as an ambiguous indicator of movement.

Future research should validate the number of clusters with cluster-validity indices, complement final stock with turnover-based measures, compare FCM with FSN analysis and other clustering methods, and use longer, multi-business datasets that include lead time, purchase cost, and seasonality.

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