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# DATA-DRIVEN CONSUMER SEGMENTATION APPROACH FOR JEANS RETAIL SALES USING FUZZY C-MEANS CLUSTERING

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**Abstract**

The fashion retail industry generates large volumes of sales transaction data containing valuable information regarding consumer purchasing behavior and preferences. However, extracting meaningful insights from heterogeneous retail data remains challenging when using conventional analytical approaches. This study aims to analyze jeans sales transaction data and identify consumer purchasing patterns using the Fuzzy C-Means (FCM) clustering algorithm. The proposed approach adopts the Knowledge Discovery in Databases (KDD) framework, consisting of data selection, preprocessing, transformation, data mining, and evaluation stages to ensure systematic analysis. The dataset used in this study consists of 799 jeans sales transaction records collected in 2024 from Shakila Collection, involving four attributes: product name, payment method, price, and purchase quantity. To improve clustering effectiveness, only price and purchase quantity were selected as the primary variables due to their relevance in representing consumer purchasing behavior. Clustering performance was evaluated using the Davies-Bouldin Index (DBI) to determine the optimal number of clusters. Experimental results show that the best clustering configuration was achieved at $k = 3$, producing three consumer segments consisting of 175 items in Cluster 0, 590 items in Cluster 1, and 34 items in Cluster 2. The findings indicate that medium-priced products tend to have higher purchasing intensity and more flexible purchase quantities, whereas premium-priced products exhibit relatively lower demand. The novelty of this study lies in integrating Fuzzy C-Means clustering with consumer preference analysis to generate practical business insights for pricing strategies, inventory optimization, and targeted marketing, thereby supporting more effective data-driven decision-making in fashion retail businesses.

**Keywords**: fuzzy c-means; consumer preference; fashion retail; data mining; knowledge discovery in databases (KDD).

## 1. INTRODUCTION

The fashion industry is one of the sectors experiencing rapid growth due to changing lifestyles and increasingly dynamic consumer preferences. Among fashion products, jeans remain one of the most demanded commodities because of their versatility, durability, and ability to adapt to evolving market trends. In the context of fashion retail business, sales transaction data contain valuable information regarding consumer purchasing behavior, preferences, and demand patterns. However, the increasing volume and heterogeneity of sales data often make conventional analytical methods insufficient for extracting meaningful insights effectively. Therefore, a data-driven approach based on data mining techniques is required to identify hidden patterns and support more informed business decision-making.

Clustering is one of the most widely applied techniques in data mining for grouping data based on similarity characteristics. One of the prominent clustering algorithms is the Fuzzy C-Means (FCM) algorithm, which is widely recognized for its ability to handle uncertainty in complex datasets through membership degrees assigned to each cluster. Unlike K-Means, which applies a strict (hard clustering) assignment, FCM allows a data point to belong to multiple clusters simultaneously, thereby providing greater flexibility in representing overlapping and uncertain consumer behavior patterns [1]. Furthermore, recent studies have shown that FCM contributes significantly to improving clustering quality and can be optimized to enhance computational efficiency and analytical accuracy in large-scale datasets [2].

Several previous studies have explored the implementation of Fuzzy C-Means across different domains. Research conducted by Sultan et al. (2024) applied FCM to vehicle sales data and compared it with DBSCAN, demonstrating that clustering techniques can generate meaningful insights for sales analysis [3]. Similarly, Babu et al. (2024) employed FCM for customer segmentation in shopping centers and successfully identified consumer behavior patterns from transaction data [4]. Another study by Putra and Abdulloh (2024) compared FCM with K-

Means and DBSCAN for product clustering based on pricing and specifications, concluding that FCM offers greater stability in handling complex data distributions [5]. In addition, Suryadi (2024) reported that FCM provides more adaptive clustering results for datasets with high variability compared to conventional clustering approaches [6].

Despite these advancements, there remains a significant research gap in the application of Fuzzy C-Means to fashion retail sales analysis, particularly for jeans products characterized by dynamic demand patterns and trend-driven purchasing behavior. Most previous studies have focused primarily on algorithm comparison or general clustering applications without explicitly linking clustering outcomes to consumer preference analysis as a strategic basis for business decision-making. Moreover, limited studies have specifically investigated sales segmentation in the jeans retail sector using fuzzy clustering approaches to support inventory optimization and targeted marketing strategies [7].

The novelty of this study lies in the integration of Fuzzy C-Means clustering with consumer preference analysis in jeans sales data to generate actionable business insights. Unlike prior studies that primarily emphasize clustering performance evaluation, this research focuses on interpreting clustering results to understand purchasing patterns and consumer preferences, thereby providing practical implications for marketing strategies, inventory management, and customer satisfaction improvement. In addition, this study employs the Knowledge Discovery in Databases (KDD) framework to ensure a systematic data mining process, ranging from data preprocessing to clustering evaluation.

Based on this background, this study aims to analyze jeans sales data using the Fuzzy C-Means algorithm to identify purchasing patterns and consumer preferences. It is expected that the findings will contribute both theoretically and practically by providing a more adaptive analytical approach to sales data analysis and generating meaningful information to support strategic decision-making in marketing, stock management, and customer relationship enhancement in the fashion retail industry[8]. Another novelty of this research lies in the utilization of clustering outputs as a decision-support mechanism for consumer-oriented business strategies in the jeans retail sector. Unlike previous studies that mainly focus on cluster formation and performance comparison, this study emphasizes the interpretation of cluster characteristics based on price and purchase quantity to identify distinct purchasing segments and market tendencies. The resulting clusters are not only evaluated statistically but are also translated into practical business recommendations, such as product positioning, promotional strategies, and inventory prioritization. This approach strengthens the practical relevance of clustering analysis by bridging the gap between computational modelling and managerial decision-making in fashion retail businesses.

## 2. RESEARCH METHODS

This study aims to cluster fashion sales data, specifically jeans products, to identify purchasing patterns and consumer preferences using the Fuzzy C-Means (FCM) algorithm. The primary problem addressed in this research concerns how complex and uncertain sales data can be grouped into representative clusters capable of generating meaningful insights for business decision-making processes[9]. Since consumer purchasing behavior in the fashion retail sector is often dynamic and heterogeneous, an adaptive clustering approach is required to capture hidden patterns and segment consumer characteristics more effectively. The research methodology adopts the Knowledge Discovery in Databases (KDD) framework, which provides a systematic approach for extracting meaningful information from large datasets. The KDD process in this study consists of five stages: data selection, preprocessing, transformation, data mining, and evaluation. The dataset used comprises 799 jeans sales transaction records obtained from a fashion retail store, with price and purchase quantity selected as the primary variables for clustering analysis. These attributes were chosen because they directly represent purchasing behavior and product demand intensity, which are essential for understanding consumer preferences in retail transactions[10].

### 2.1. Problem Formulation

Given a dataset represented as:

$$X = \{x_1, x_2, x_3, \dots, x_n\} \qquad (1)$$

where $n$denotes the total number of data points, the objective of clustering is to partition the dataset into $c$clusters based on similarity characteristics among observations. In the Fuzzy C-Means (FCM) approach, each data point is assigned a degree of membership to every cluster rather than being strictly assigned to a single cluster, allowing more flexible representation of uncertain and overlapping data distributions[11].

### 2.2. Fuzzy C-Means Algorithm

The Fuzzy C-Means (FCM) algorithm is a soft clustering technique that enables a single observation to belong to multiple clusters simultaneously through membership values ranging from 0 to 1. This characteristic makes FCM particularly suitable for analyzing consumer purchasing behavior, where transaction patterns may overlap across different consumer segments.

The objective function of the FCM algorithm is formulated as follows[12]–[14]:

$$J_m = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^m \left\| x_i - v_j \right\|^2 \qquad (2)$$

where:
$J_m$= objective function value,
$u_{ij}$= membership degree of the $i$-th data point in the $j$-th cluster,
$m$= fuzziness parameter ($m > 1$),
$x_i$= the $i$-th data point,
$v_j$= centroid of the $j$-th cluster.

The cluster centroid is calculated using the following equation:

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \qquad (3)$$

Meanwhile, the membership degree is updated iteratively using:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{\left\| x_i - v_j \right\|}{\left\| x_i - v_k \right\|} \right)^{\frac{2}{m-1}}} \qquad (4)$$

The iterative process continues until convergence criteria are achieved, which occurs when the difference in the objective function value or the membership matrix falls below a predefined threshold [15], [16].

### 2.3. Research Procedure

The research procedure follows the stages of the KDD framework, which are described as follows:

a. Data Selection
Selection of relevant jeans sales transaction data, focusing on attributes related to purchasing behavior, namely price and purchase quantity.
b. Preprocessing
Data cleaning was conducted to remove inconsistencies, detect missing values, and normalize numerical attributes to improve clustering performance.
c. Transformation
The selected variables were transformed into a suitable numerical representation to ensure compatibility with the FCM algorithm.
d. Data Mining
Implementation of the Fuzzy C-Means algorithm to group transaction data into representative clusters based on similarity patterns.
e. Evaluation
Evaluation of clustering performance using the Davies-Bouldin Index (DBI) to determine the optimal number of clusters and assess cluster quality.

### 2.4. Model Evaluation

The quality of clustering results was evaluated using the Davies-Bouldin Index (DBI), a widely used internal validation metric for measuring cluster compactness and separation. DBI assesses the similarity within clusters and the distinction between clusters simultaneously. A lower DBI value indicates better clustering performance, reflecting more compact intra-cluster similarity and clearer inter-cluster separation. Through this evaluation process, the study aims to obtain an optimal clustering structure capable of providing accurate and meaningful insights into consumer purchasing patterns and preferences in the fashion retail sector[17].

## 3. RESULTS AND DISCUSSION

### 3.1. Dataset Description

This study analyzes jeans sales transaction data obtained from Shakila Collection, consisting of 799 transaction records collected in 2024. The dataset was obtained in Microsoft Excel (.xls) format and contains four primary attributes: product name, payment method, price, and purchase quantity. To provide an overview of the dataset characteristics, a sample of ten transaction records is presented in Table 1.

Table 1. Sample of Jeans Sales Dataset

| No | Product Name | Payment Method | Price | Quantity |
|---|---|---|---|---|
| 1 | Levi's 511 Slim Fit | tf | 120 | 3 |
| 2 | Wrangler Regular Fit | cod | 135 | 2 |
| 3 | Lee Cooper Straight Jeans | cod | 140 | 4 |
| 4 | Zara Denim Basic | tf | 150 | 2 |
| 5 | H&M Slim Jeans | tf | 145 | 5 |
| 6 | Uniqlo Stretch Denim | cod | 130 | 2 |
| 7 | Pull & Bear Skinny Jeans | tf | 155 | 1 |
| 8 | Nevada Relaxed Fit Jeans | cod | 125 | 6 |
| 9 | Lois Classic Jeans | cod | 160 | 2 |

### 3.2. Data Selection and Preprocessing

The dataset selection stage focused on jeans sales transaction data collected during 2024 from Shakila Collection. Initially, the dataset contained four attributes, namely product name, payment method, price, and quantity, as shown in Table 2.

Table 2. Initial Dataset Attributes

| No | Attribute | Data Type | Description |
|---|---|---|---|
| 1 | Product Name | Nominal | Product identifier |
| 2 | Payment Method | Nominal | Transaction payment type |
| 3 | Price | Numerical | Product price |

The dataset was imported into RapidMiner Studio version 9.9.2 using the Read Excel operator, as illustrated in Figure 1. Statistical information generated from the dataset was subsequently examined to identify inconsistencies, outliers, and missing values.

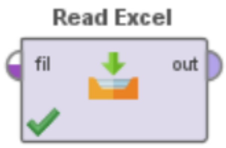


Figure 1. Read Excel operator

During the preprocessing stage, data cleansing procedures were conducted to ensure data consistency and quality. The dataset was examined for missing values and inconsistent entries. The analysis revealed that the dataset contained consistent transaction records without significant missing values that could affect clustering performance. To improve clustering efficiency, attribute selection was performed using the Select Attributes operator. Since the purpose of clustering was to analyze purchasing behavior based on economic purchasing tendencies, only price and purchase quantity were selected as clustering variables, while product name and payment method were excluded because they were considered categorical identifiers and not directly relevant to numerical distance calculations.

Table 3. Selected Attributes for Clustering.

| No | Attribute | Data Type | Description |
|---|---|---|---|
| 1 | Price | Numerical | Product selling price |

### 3.3. Fuzzy C-Means Clustering Implementation

The clustering process was implemented using the Fuzzy C-Means (FCM) algorithm in RapidMiner Studio version 9.9.2, as shown in Figure 2. The FCM algorithm was selected due to its ability to assign membership values to multiple clusters, thereby providing greater flexibility in handling uncertain and overlapping purchasing patterns.
To evaluate clustering performance, the Cluster Distance Performance operator was employed. This operator was used to measure clustering quality and identify the optimal number of clusters through the Davies-Bouldin Index (DBI). Several clustering experiments were conducted by varying the number of clusters from $k = 2$ to $k = 10$. Based on the evaluation results, the optimal clustering configuration was obtained at $k = 3$, which produced the best clustering performance according to the DBI criterion.

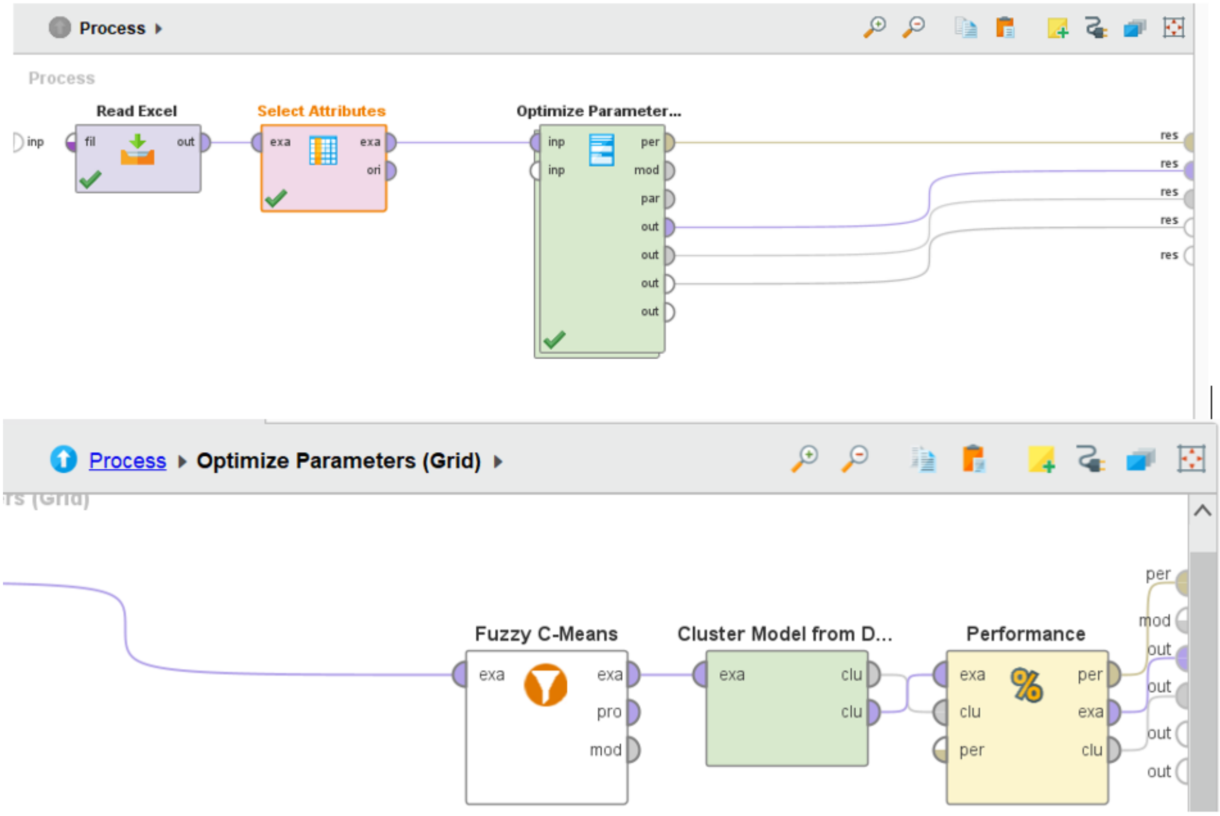


Figure 2. Fuzzy C-Means (FCM) algorithm in RapidMiner Studio

Figure 2 illustrates the workflow of the clustering process used for jeans sales data analysis with the Fuzzy C-Means (FCM) algorithm. The process begins with the Read Excel operator, which is used to import the sales dataset in Excel format into the analysis environment. Subsequently, the Select Attributes operator is applied to select relevant variables, specifically price and quantity, while excluding attributes that are not directly relevant to clustering analysis. The selected data are then processed through the Optimize Parameters (Grid) operator to determine the optimal clustering configuration by evaluating multiple parameter combinations. Within this stage, the Fuzzy C-Means operator performs the clustering process, followed by the Cluster Model and Performance operators, which evaluate clustering quality and identify the most appropriate cluster configuration. The final clustering model generated three clusters consisting of 175 items in Cluster 0, 590 items in Cluster 1, and 34 items in Cluster 2, resulting in a total of 799 clustered transaction records. This workflow ensures a systematic clustering process and improves the reliability of consumer segmentation results.

### 3.4. Clustering Performance Evaluation

The clustering results were evaluated using the Davies-Bouldin Index (DBI), which measures intra-cluster similarity and inter-cluster separation. Lower DBI values indicate better clustering performance due to stronger compactness within clusters and clearer separation among clusters. The evaluation process showed that the optimal clustering model consisted of three clusters (k = 3), which achieved the best clustering performance. Furthermore, each cluster demonstrated different centroid characteristics, indicating variation in purchasing behavior among customer groups. The resulting cluster composition revealed a dominant concentration in Cluster 1, which contained 590 transaction records, followed by Cluster 0 with 175 records, and Cluster 2 with 34 records. This distribution suggests that consumer purchasing behavior is primarily concentrated within a specific purchasing segment.

### 3.5. Price–Quantity Visualization Analysis

The Price versus Quantity visualization was used to analyze the relationship between product price and purchase quantity. The scatter plot, shown in Figure 3, illustrates the clustering results based on the variables price (X-axis) and quantity (Y-axis). The visualization indicates that Cluster 1 (blue) is concentrated in the medium-price range with varying purchase quantities, suggesting relatively stable and flexible consumer demand. Meanwhile, Cluster 0 (green) is positioned within a higher price range with moderate purchasing quantities, indicating products with moderate market interest. In contrast, Cluster 2 (orange) consists of high-priced products with relatively lower purchasing quantities, reflecting lower purchasing frequency.An observable pattern indicates an inverse relationship between price and purchase quantity, where higher-priced products tend to exhibit lower purchase quantities. This finding aligns with consumer purchasing behavior theory, in which pricing significantly influences purchasing decisions.


Figure 3. Price–Quantity Clustering Visualization Using Fuzzy C-Means

Figure 3 illustrates the clustering results of jeans sales transactions based on the relationship between price and purchase quantity using the Fuzzy C-Means (FCM) algorithm. The scatter plot demonstrates how transaction data are distributed into three distinct clusters, namely cluster_1 (blue), cluster_0 (green), and cluster_2 (orange), based on similarities in purchasing behavior. The X-axis represents product price, while the Y-axis indicates the quantity of items purchased in each transaction. Each point in the visualization corresponds to a single sales transaction record, enabling a clearer understanding of consumer purchasing tendencies according to different price levels. The visualization reveals that cluster_1 (blue) dominates the dataset and is concentrated primarily within the price range of approximately 44–52, with purchase quantities varying widely from 1 to 6 units. This cluster indicates a segment of products with moderate pricing and flexible purchasing intensity, suggesting that products within this range are more attractive to consumers and exhibit stronger purchasing demand. The high concentration of transaction points in this cluster also indicates that most consumer purchasing behavior is centered around medium-priced jeans products, making this segment a potentially important target for inventory optimization and customer retention strategies.

Meanwhile, cluster_0 (green) is distributed within a relatively higher price range, approximately 58–62, with purchase quantities generally ranging from 1 to 6 units, although transactions are more concentrated at lower quantities. This cluster represents products with higher prices but still maintaining moderate consumer demand, indicating a relatively stable market segment. Consumers in this category may prioritize factors such as product quality, brand value, or product exclusivity over price sensitivity. Therefore, products within this cluster may benefit from premium positioning strategies while maintaining adequate stock availability.

In contrast, cluster_2 (orange) is concentrated at the highest price range, approximately 64–70, and exhibits consistently low purchase quantities, mostly between 1 and 2 units per transaction. This pattern suggests that high-priced jeans products tend to experience lower purchasing frequency, reflecting more selective consumer behavior and lower market demand. The limited distribution of data points in this cluster indicates a niche or premium market segment that may require targeted promotional efforts, discount strategies, or specialized marketing approaches to improve purchasing interest.

Overall, the visualization demonstrates an observable inverse relationship between product price and purchase quantity, where products with higher prices tend to have lower purchase volumes. This finding aligns with the general economic principle of consumer demand, in which price increases may reduce purchasing intensity. Furthermore, the clustering results successfully segment consumer purchasing behavior into three meaningful groups, providing valuable insights for pricing strategies, inventory planning, market segmentation, and customer preference analysis in the fashion retail sector.

### 3.6. Consumer Purchase Grouping and Business Implications

The clustering results provide meaningful insights into consumer purchasing preferences and product segmentation strategies. Cluster 1, containing 590 transaction records, represents products with moderate prices and relatively higher purchasing intensity. This cluster indicates products with stronger consumer demand and may support inventory optimization strategies to maintain stock availability and customer satisfaction. Cluster 0, consisting of 175 records, represents products within a higher price range but still exhibiting moderate purchasing levels. This cluster may indicate products with stable profitability potential, requiring balanced pricing and marketing strategies to maximize revenue. Meanwhile, Cluster 2, containing only 34 records, represents premium-priced products with relatively low purchasing quantities. This cluster may require targeted promotional strategies, discount programs, or product repositioning to increase consumer interest and reduce the risk of inventory accumulation. Overall, the clustering analysis successfully segmented jeans sales data into three major consumer groups, enabling businesses to better understand purchasing patterns and design more targeted marketing, pricing, and inventory management strategies.

### 3.7. Discussion

The clustering results obtained using the Fuzzy C-Means (FCM) algorithm demonstrate that jeans sales transaction data can be effectively grouped into three distinct consumer segments based on the variables of price and purchase quantity. The evaluation process identified three clusters ($k = 3$) as the optimal grouping configuration, consisting of 175 items in Cluster 0, 590 items in Cluster 1, and 34 items in Cluster 2. The dominance of Cluster 1 indicates that consumer purchasing behavior is primarily concentrated within a specific price segment, suggesting that medium-priced products tend to attract broader consumer interest. This finding reflects the heterogeneous nature of purchasing behavior in fashion retail, where different pricing levels correspond to varying consumer preferences and purchasing intensities.

The visualization of the clustering results reveals a meaningful relationship between price and quantity, where products with moderate price levels exhibit greater purchasing variability compared to high-priced products. Cluster 1, which contains the largest number of transaction records, represents products within a medium price range and displays relatively flexible purchase quantities. This suggests that products in this segment are more adaptable to different consumer purchasing capacities and preferences, making them highly relevant for inventory prioritization and demand forecasting. The concentration of transactions within this cluster further implies that consumers tend to prefer products offering a balance between affordability and perceived product value.

Meanwhile, Cluster 0 represents products within a relatively higher price range but still maintains moderate purchasing quantities. This indicates that although price may influence consumer purchasing decisions, certain products continue to attract stable demand due to other contributing factors such as product quality, brand reputation, design preferences, or customer loyalty. Therefore, this segment may represent products with stable profitability potential, where maintaining product quality and effective positioning strategies become essential to sustain market competitiveness.

In contrast, Cluster 2, which contains the fewest transaction records, represents premium-priced products with relatively low purchasing quantities. The low density of transaction points in this cluster indicates more selective purchasing behavior and lower consumer demand for highly priced products. This condition suggests that premium products may require more targeted marketing interventions, such as personalized promotions, discount campaigns, or product bundling strategies to improve consumer engagement. Furthermore, the presence of a smaller niche segment implies opportunities for businesses to better understand premium consumer preferences and optimize market positioning strategies.

Overall, the clustering analysis confirms that the Fuzzy C-Means algorithm is capable of identifying hidden purchasing patterns within jeans sales data and generating meaningful consumer segmentation. The findings contribute not only to understanding consumer purchase behavior but also to supporting strategic business decisions related to pricing optimization, stock management, customer segmentation, and targeted marketing strategies. By transforming transaction data into actionable insights, businesses can improve operational efficiency and respond more adaptively to dynamic consumer preferences in the fashion retail sector.

## 4. CONCLUSION

This study successfully applied the Fuzzy C-Means (FCM) algorithm to cluster jeans sales transaction data and identify consumer purchasing patterns based on price and purchase quantity variables. The clustering process, conducted using RapidMiner Studio version 9.9.2 and evaluated through the Davies-Bouldin Index (DBI), indicated that the optimal clustering configuration consisted of three clusters. The clustering results produced 175 transaction records in Cluster 0, 590 records in Cluster 1, and 34 records in Cluster 2, demonstrating different levels of consumer purchasing behavior across product price ranges. The findings reveal that products within the medium-price range tend to dominate consumer purchases and exhibit more flexible purchasing quantities, indicating stronger market demand. Meanwhile, products in higher price ranges showed relatively lower purchasing intensity, suggesting the existence of selective consumer behavior toward premium-priced products. These results indicate that pricing significantly influences purchase quantity and consumer preferences in the fashion retail sector. The implementation of the Fuzzy C-Means algorithm proved effective in identifying hidden purchasing patterns and generating meaningful consumer segmentation from sales transaction data. The resulting clusters provide practical insights that may support business decision-making, particularly in pricing strategies, inventory optimization, product positioning, and targeted marketing initiatives. By utilizing clustering-based consumer segmentation, fashion retailers may better adapt to dynamic consumer preferences and improve operational efficiency. Nevertheless, this study has several limitations.

The analysis was conducted using only two variables, namely price and purchase quantity, which may not fully represent consumer purchasing behavior. Future studies are recommended to incorporate additional attributes such as product category, brand preference, purchase frequency, seasonal trends, and payment methods to generate more comprehensive consumer segmentation. Furthermore, future research may compare the performance of Fuzzy C-Means with other clustering algorithms, such as K-Means, DBSCAN, or hierarchical clustering, to evaluate clustering effectiveness across different retail data characteristics.

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