
Sailfish Optimizer Driven Framework for Mining Dynamic Consumer Purchase Patterns

Ahmed Al-Khafaji

*Department of Computer Science,
University of Baghdad,
Al-Jadriya Campus, Baghdad, Iraq*

&

Rasha Al-Dulaimi

*Faculty of Engineering and Computer Science,
University of Anbar,
Ramadi, Iraq.*

ABSTRACT

Mining dynamic consumer purchase patterns is crucial for understanding shifting market trends and improving personalized marketing strategies. The proposed framework leverages the Sailfish Optimizer to intelligently mine and adapt to evolving consumer behaviors. Existing methods often struggle with high-dimensional, non-linear, and time-varying consumer data, resulting in suboptimal clustering accuracy and slow adaptation to dynamic changes. To address these limitations, this paper introduces the Sailfish Optimizer-Based Fuzzy Clustering Means (SFO-FCM) framework, where the Sailfish Optimizer fine-tunes the fuzzy clustering parameters to achieve optimal performance. The framework effectively segments consumer data into adaptive clusters by balancing exploration and exploitation, allowing more accurate tracking of evolving purchase patterns. This optimized clustering is then used to generate actionable insights, such as real-time personalized offers and inventory management strategies in retail systems. Experimental results demonstrate that the proposed SFO-FCM framework outperforms conventional FCM. The proposed SFO-FCM achieves a clustering accuracy of 89.4%, a precision of 86.0%, a recall of 88.4%, an F1-score of 0.87, and a computation time of just 9.1 seconds. Additionally, it attains a high NMI score of 0.77, and other metaheuristic-based approaches in terms of clustering accuracy, adaptability, and computational efficiency, making it well-suited for dynamic and large-scale e-commerce environments.

Keywords: Consumer Purchase Patterns, Sailfish Optimizer, Fuzzy C-Means, Dynamic Clustering, E-commerce Analytics, Behavioral Segmentation.

1. Introduction

Consumer purchasing behavior is crucial in understanding the modern data landscape. Knowledge of consumer purchasing behavior is essential for firms looking to compete and deliver personalized services [1]. Consumer purchasing behavior is constantly changing in response to time-sensitive situations, such as seasonal purchasing, stock limitations, or abundance due to promotions, economic and monetary fluctuations, and the ever-evolving preferences of individuals. Most data mining methods assume that the underlying data is stationary and linear [2]. Therefore, it is not an optimal way to work with evolving instability and non-linear consumer purchase behaviors. Recognizing the growing importance of time-sensitive purchasing patterns, practitioners are seeking more adaptable and intelligent frameworks to analyze evolving purchasing styles derived from large and high-dimensional datasets [3].

Clustering is a well-known non-supervised machine learning technique commonly used to segment customers, allowing companies to group customers based on their similar behavior, effectively market to them, make recommendations, and aid in inventory forecasting [4]. However, while traditional clustering algorithms, such as k-means and standard FCM, can be powerful tools for segmenting customers, they rely on static initialization and are highly sensitive to data distribution and noise in dynamic environments [5]. Commonly used clustering algorithms often fail to converge at global maxima due to local minima, and they frequently fail to capture the dynamic nature of evolving consumer behavior adequately. In response to the limitations outlined above, this paper presents an SFO Framework for enhancing the fuzzy clustering mechanism to mine Dynamic Consumer Purchase Patterns [6]. SFO is a newly developed population-based metaheuristic that is driven by observing the predation dynamics between sailfish and sardines and attempts to imitate these dynamics in variable dimensions. SFO performs exceptionally well in balancing exploration and exploitation when solving high-dimensional optimization problems that utilize chaotic search landscapes [7]. Combining SFO with FCM yields a superior clustering mechanism, enabling SFO to optimize the centroid locations and fuzzification coefficient with significantly higher accuracy and a lower degree of volatility over time.

The SFO-FCM framework suggests that clusters can be updated in real-time using consumer transactional data streams. Real-world scenarios often involve multiple types of time-based consumer behaviors, so clustering parameters are recalibrated to accommodate long-term variabilities in similar consumer behaviors using SFO, ensuring it remains in a state of sensing real-time movement in patterns [8]. The SFO-FCM framework is beneficial in cases, such as when a consumer is shopping online, where the user experience is determined by the rapidly changing preferences and behaviors of consumers based on seasonal patterns, recommendations, and promotional sales. A practical application of this framework can be seen in how the system can generate personalized retail promotional information fully autonomously. Identifying consumer groups that have behaved similarly with a changing interest base and sending out promotional material in the same general timeframe after identifying reasonably similar clusters of consumers [9]. It is also worth noting that the insights derived from the optimized clusters can be leveraged to facilitate other processes, including dynamic pricing scenarios, supply chain forecasting, cross-selling opportunities, and various other significant data-driven initiatives [10].

Problem Statement

Traditional clustering methods struggle to accurately capture evolving consumer purchase patterns due to static parameters and local optima, necessitating a dynamic, adaptive framework optimized for real-time, non-linear behavioral data analysis.

The main contribution of this paper is:

- A novel Sailfish Optimizer-enhanced fuzzy clustering method that adaptively captures evolving consumer purchase patterns in dynamic environments, outperforming conventional clustering techniques in stability and accuracy.
- The proposed framework enables real-time segmentation of consumer behavior by continuously updating clusters, ensuring accurate reflection of changing purchase patterns and supporting timely marketing interventions.
- This paper demonstrates the effectiveness of the SFO-FCM framework in optimizing personalized retail promotion strategies, improving recommendation relevance, customer engagement, and business revenue in dynamic e-commerce settings.

A summary of the research is provided below. In Section 2, literature review and study techniques are thoroughly examined. The SFO-FCM framework is detailed in Section 3. The results and discussion are covered in Section 4. Part 5 explores the main conclusion and future work.

2. Literature Review

According to Adiputera et al. [11], companies are faced with both challenges and opportunities as a result of the extraordinary rise of customer transaction data caused by the e-commerce industry's fast expansion. In this paper look at how the Association Rule Mining (ARM) algorithm may be used to study customer buying habits and find hidden connections between often bought goods. This article shows that e-commerce platforms may boost revenues by using ARM to make products more personalized, expand cross-selling opportunities, and engage customers more.

Financial institutions developed by Abbasimehr et al. [12] use data mining and BI methods to study client habits. Customer segmentation that aids in identifying and informing diverse groups of consumers is an example of an analytical approach. Created a system that implements consumer segmentation using time-series Clustering Algorithms (CA) after representing customer behavior as a time-series sequence of the three variables RFM (Recency, Frequency, Monetary). Hierarchical clustering using the Complexity-Invariant Distance measure yields the best clustering model for grocery merchants, according to the computed validity indices. Appliance merchants use spectral clustering using the same metric to establish their segmentation.

The paper conducted by Ahmed and colleagues [13] provide a collaborative approach to data clustering that does not involve sharing raw data. This method makes use of a federated learning framework and an attention-based paradigm. An attention model which offers a low-dimensional embedding is trained using the transaction data. In order to implement clustering utilizing efficient pattern mining approaches, particularly the Clustering-Based Dynamic Method (CBDMD), may first share our convergence model with the client/stores. Clustered consumers based on buy membership using retail shop data for testing reasons. Semantic embedding was used by the suggested cluster technique to first extract and then group clients according to shared patterns.

In order to find useful information included within Typical Electricity Load Patterns (TELPs), Liu et al. [14] provide a generic framework that employs data mining methods. The three main components of the framework are data preparation, TELP identification, and knowledge discovery. These components include several data mining approaches. The framework was used to examine time series data on power usage from three operational office buildings in Chongqing, and the results were proven to be realistic. We discussed one possible use of the new information: spotting anomalous electrical load profiles early on at the building level and fixing them before they cause problems. An effective way to educate building managers on the features of a facility's electrical consumption and to identify outliers is the suggested framework.

Ebrahimi et al. [15] set out to determine the characteristics and methods of content delivery for social network marketing communications. Customers' buying habits might be impacted. Our study stands out from the crowd because to its innovative approach, which combines Structural Equation Modeling (SEM) with unsupervised machine learning methods. Users from Hungary who utilize Facebook Marketplace made up the study's statistical population. In this study, the authors used the convenience sampling technique to choose their participants as accurately as possible. This study's findings show that Facebook Marketplace customers are greatly influenced by social network marketing strategies that include entertainment, personalization, engagement, and trends.

According to Alsayat et al. [16], user-generated content and big social data have become indispensable resources for obtaining up-to-date, detailed information on consumer habits. Finding a way to quantify the value that user-generated content adds to the bottom line is a major challenge for businesses operating in the travel and hospitality industry. We go over the results and what they mean, including the theoretical contributions and various recommendations and tactics for hotel managers to boost customer happiness and service quality.

Web data mining, as shown by Ravinder et al. [17], is now an easy and crucial way to find and identify valuable information. The World Wide Web immediately springs to mind as the starting point or channel for file transfers. Discovering helpful information and design trends on the web is become more and more of a chore as the amount of relevant data grows. Using the Naive Bayes approach for online data mining has its benefits when dealing with the massive volumes of textual data often found on the web.

According to Shu et al. [18], the problem of large data prompted the development of the multidisciplinary field of knowledge discovery and data mining, which employs a variety of analytical

techniques to unearth previously unknown information in the field of data mining. The new method is a dialectical study technique that combines inductive and deductive reasoning. Data mining also takes into account additional joint, interactional, and independent predictors automatically or semi-automatically to improve prediction efficiency and handle causal heterogeneity.

Data mining, as shown by Sirichanya et al. [19], is the process of uncovering previously unknown patterns or useful information in datasets. When it comes to conceptual or semantic interpretation of data, traditional data-mining methods that rely on statistical computations, machine learning, AI, and database technologies often fall short. As a result, the hidden meanings within the data remain hidden. A user is not studied and its importance and ramifications are determined as a result of this. Over the last decade, a number of semantic data-mining methods have been suggested that use a domain ontology as a foundation for knowledge to improve data-mining performance, thereby overcoming these restrictions.

Using smart meters installed in around 1,000 Hungarian homes, Vamos et al. [20] assembled a detailed electric load dataset with high precision. Many of these families lived in detached houses. Using time series of daily and yearly electric demand, this article sought to conduct a fine-grained analysis of this information in order to outline energy consumption patterns. After ensuring that the dataset was representative, three distinct clustering approaches were used to generate energy consumption profiles on a daily and annual basis: k-means, fuzzy k-means, and agglomerative hierarchical.

3. A Model for SFO-FCM

The section describes the SFO-FCM model, which was developed to detect evolving consumer purchase patterns dynamically. In this section, the process of adaptive clustering and the application of SFO-FCM for real-time, personalized promotional retail communications to consumers are discussed. The behavior of optimized segmentation and its role in enabling marketers and organizations to make data-driven marketing decisions, thereby allowing them to address consumers more accurately in dynamic environments, will be highlighted.

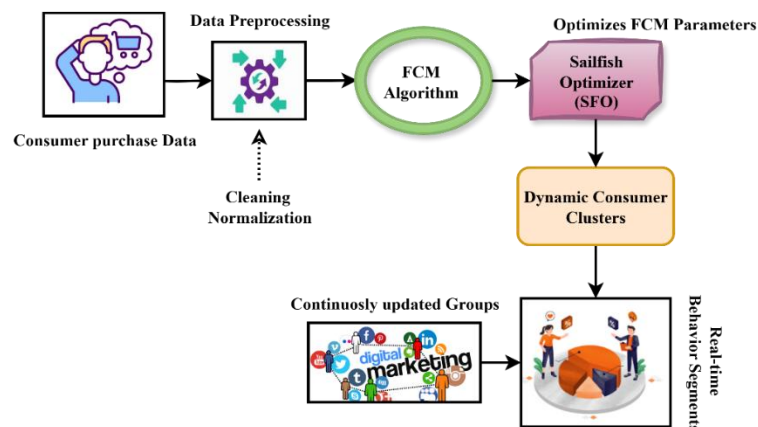


Figure 1: SFO-Enhanced Adaptive Clustering Framework

Figure 1 displays the process flow for the SFO-FCM framework for mining dynamic consumer purchase patterns. It starts with consumer purchase data, and this data is subject to preprocessing (cleaning and normalizing of data values) as part of the data preparation step. Once the data has been pre-processed, the prepared consumer purchase data is passed into the FCM clustering algorithm. The first process in the FCM clustering is clustering consumer behavior. To dynamically enhance the accuracy of the FCM process and retain flexibility, the SFO optimizes the FCM parameter values in real-time to improve clustering quality. The dynamic clusters generated in the final step form dynamic

consumer clusters that reflect shifting consumer purchasing patterns. The dynamic clusters are then grouped in real-time for a cluster in tandem with existing behavioral segments. This process advances the marketing firms' techniques and subsequent measurement of evolving (changing) customer profiles for real-time adjustments to marketing approaches.

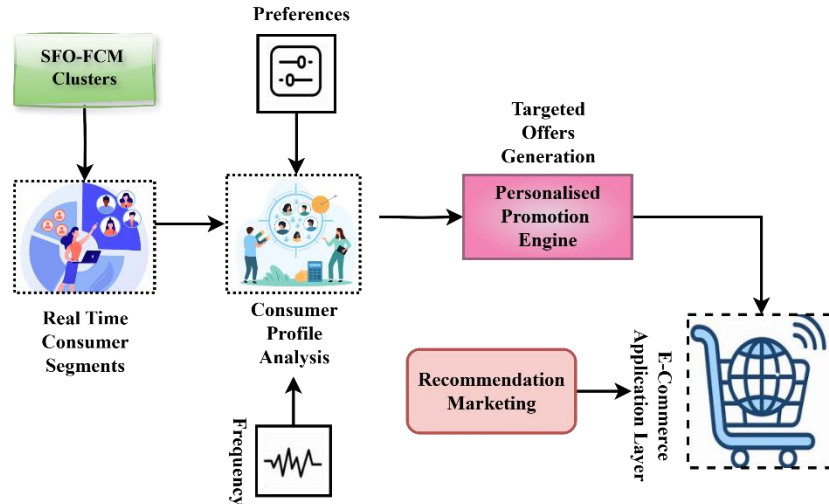


Figure 2: Application in Personalized Retail Promotions

Figure 2, depicted above, demonstrates the application layer of the SFO-FCM framework's capabilities in a retail setting. Based on real-time consumer segments derived from optimized clustering, the framework utilizes information from consumer profile analysis to provide insights into consumer preferences, shopping frequency, and shopping behavior, among other factors. The personalized promotion engine leverages these insights to deliver optimally targeted offers, explicitly tailored to each segment. The result is delivered through the e-commerce application layer, where customized recommendations and marketing campaigns are executed. This enables a seamless integration between evolving consumer behavior and identifying and responding to it, thereby enhancing customer engagement, satisfaction, and conversion rates in a fast-paced retail environment.

Algorithm 1: Compute Clustering Accuracy (DB) for SFO-FCM

INPUT:

C = Total number of true class labels

∂ = 2D matrix of fuzzy membership counts $[\partial_{jk}]$ for each class j and cluster k

μ = 3D matrix μ_{jkl}

→ count of correctly classified instances in (class j , cluster k , dimension l)

τ = 3D matrix τ_{jkl}

→ count of wrongly classified instances in (class j , cluster k , dimension l)

ρ = Regularization constant (e.g., 1.0)

σ = Small constant to avoid division by zero (e.g., $1e-6$)

ε = Dimensionality of the consumer feature vector space

Function computeClusteringAccuracy($C, \partial, \mu, \tau, \rho, \sigma, \varepsilon$):

Initialize $DB_sum = 0$

Iterate over each actual class label j

For j from 1 to C :

max_value = -infinity

For each cluster k , calculate confidence value

```

For k in range of clusters:
     $\partial_{jk} = \partial[j][k]$ 
    numerator_sum = 0
    denominator_sum = 0

    Sum over feature vector dimensions l
    For l from 1 to  $\varepsilon$ :
        numerator_sum +=  $\mu[j][k][l]$ 
        denominator_sum +=  $\tau[j][k][l]$ 

    Avoid division by zero
    If  $(\sigma + \text{denominator\_sum}) == 0$ :
        log_term = 0
    Else:
        ratio =  $(\rho + \text{numerator\_sum}) / (\sigma + \text{denominator\_sum})$ 
        If ratio <= 0:
            log_term = 0
        Else:
            log_term =  $\log_2(\text{ratio})$ 

    value =  $\partial_{jk} * \log\_term$ 

    Keep maximum value across all clusters for class j
    If value > max_value:
        max_value = value

    Add maximum value for class j to total DB sum
    DB_sum += max_value

Final DB accuracy score
DB = DB_sum / C
Return DB

```

The algorithm 1 calculates clustering accuracy (DB) by evaluating the highest confidence match between actual class labels and clusters. It uses fuzzy membership values and log-scaled ratios of correct to incorrect classifications across dimensions, ensuring numerical stability with conditions, and averages these values across all classes for final accuracy.

The SFO-FCM framework successfully integrates fuzzy clustering and metaheuristic optimization for online, real-time consumer segmentation. Through a unique variable-sized adaptive clustering method, coupled with targeting relevant to the specific application context of the consumer's parcels received, the application enhances recommendation relevance and timely-store marketing relevance, leading to a higher level of user participation, engagement, and retailer adaptability. The integration of fuzzy clustering, metaheuristic optimization, and targeting enables marketers to dynamically and actively adapt their marketing strategies, engaging with unique and highly individualized consumer behaviors.

a) Evaluation Metrics

Evaluation metrics are crucial for assessing the performance of any estimator, particularly the SFO-FCM framework. This study employed metrics to develop modern equations for measuring Clustering Accuracy, Precision, Recall, F1 Score, and Computation Time, which enabled the assessment of clustering efficiency, robustness, and adaptability to dynamic high-dimensional consumer purchase data.

Clustering accuracy DB is expressed using equation 1,

$$DB = \frac{1}{C} \sum_{j=1}^C \left(\max_k (\partial_{jk}) * \log_2 \left(\frac{\rho + \sum_{l=1}^{\varepsilon} \mu_{jkl}}{\sigma + \sum_{l=1}^{\varepsilon} \tau_{jkl}} \right) \right) \quad (1)$$

Equation 1 explains that the clustering accuracy is the exponential confidence of the maximum clustering match per labelling index, balanced by the total number of true labels, and is calculated by this accuracy metric.

In this C is the total number of actual class labels, ∂_{jk} is the fuzzy membership count for class and cluster, ρ is the regularization constant for upper-bound scaling, μ_{jkl} is the count of instances in the true class, assigned to the cluster and dimension, σ is the small value to avoid division by zero, τ_{jkl} is the count of wrongly classified instances in class, cluster, and dimension, and ε is the dimensionality of the consumer feature vector space.

Precision μ is expressed using equation 2,

$$\mu = \frac{1}{\omega} \sum_{k=1}^{\omega} \left(\frac{\sum_{j=1}^l \rho_{jk}}{Y + \sum_{j=1}^l (\rho_{jk} + \sigma_{jk})} \right) \quad (2)$$

Equation 2 explains that the precision is regularized by a factor of stability, which averages the ratio of successfully assigned occurrences per region to total anticipated instances.

In this ω is the number of clusters, l is the number of true classes, ρ_{jk} is the correct assignment count for the class in cluster, σ_{jk} is the incorrectly assigned instances for the class in the cluster, and Y is the normalization constant to handle sparse clusters.

Recall/sensitivity S is expressed using equation 3,

$$S = \frac{1}{l} \sum_{j=1}^l \left(\frac{\sum_{k=1}^{\partial} \rho_{jk}}{X + \sum_{k=1}^{\partial} (\rho_{jk} + \nabla_{jk})} \right) \quad (3)$$

Equation 3 explains that the recall/sensitivity quantifies how successfully the clustering framework recovers real class members of each class across clusters.

In this l is the number of actual class labels, ∂ is the number of fuzzy clusters, ρ_{jk} is the true positive count for the class in cluster, ∇_{jk} is the false negative count, and X is the numerical smoothing term for denominator stability.

F1 score ∂ is expressed using equation 4,

$$\partial = \frac{2 * \mu * S}{\rho + \mu + S} \quad (4)$$

Equation 4 explains that the F1 score is in order to avoid overfitting spikes caused by near-zero terms; the F1 score uses a harmonic mean that is augmented with balanced precision and recall.

In this μ is the precision, S is the recall, and ρ is the harmonic adjustment constant for denominator balancing.

Computation time U is expressed using equation 5,

$$U = \Delta * \left(\sum_{j=1}^{\pi} \left(\frac{o_j * \log(o_j)}{\log(\nabla_j + 1)} + \frac{n_j^\gamma}{\tau_j + 1} \right) \right) \quad (5)$$

Equation 5 explains the computation time by modeling search difficulty and membership updates every generation, weighted by difficulty scale and precision depth.

In this Δ is the system-dependent constant, π is the number of optimization generations, o_j is the population size in generation. ∇_j is the cluster granularity factor in generation, and n_j is the fuzzy membership update iterations in generation. Here γ is the non-linear penalty exponent for repeated updates, and τ_j is the entropy convergence slope in generation.

The evaluation metrics that the SFO-FCM framework offers superior clustering accuracy and a more balanced precision-recall while converging faster than traditional methods. Furthermore, the optimized equations yield optimal terms of behavior and time complexity with a fuzzy cluster, confirming the framework's ability to respond to changing consumer behavior using large-scale, time-sensitive retail purchase data.

4. Results and Discussion

This section presents a comprehensive performance analysis of the proposed SFO-FCM framework, based on the Consumer Behavior and Shopping Habits Dataset available on Kaggle. It compares the chosen evaluation metrics, such as clustering accuracy, precision, recall, F1-score, and computation time of the framework on the Consumer Behavior and Shopping dataset to those typical of other methods, showing that SFO-FCM outperforms clustering analytical capabilities while being more efficient in modeling consumer purchase behavior.

a) Dataset Description

The Consumer Behavior and Shopping Habits Dataset on Kaggle provides rich insights into customer demographics, product preferences, and shopping frequency. It supports the analysis of online and offline behavior, aiding in behavioral segmentation, targeted marketing, and trend prediction. Ideal for data-driven personalization and optimizing retail decision-making processes [21].

Table 1: Parameterized table

Attribute	Description
Dataset Name	Consumer Behavior and Shopping Habits Dataset
Source	Kaggle – Zeesolver
Total Records	~8,000 (varies slightly by version)
No. of Features	~15 (including demographic and behavioral fields)
Data Type	CSV (Structured, Tabular Format)
Key Variables	Age, Gender, Income, Shopping Frequency, Favorite Category, Spending Score, etc.
Target Usage	Customer segmentation, behavioral pattern mining, and recommendation systems

<i>Applications</i>	Market basket analysis, targeted marketing, trend analysis, and customer profiling
<i>Usability</i>	Suitable for clustering, classification, and personalization algorithms
<i>License</i>	Open (for research and non-commercial use)

b) Parameterized Values

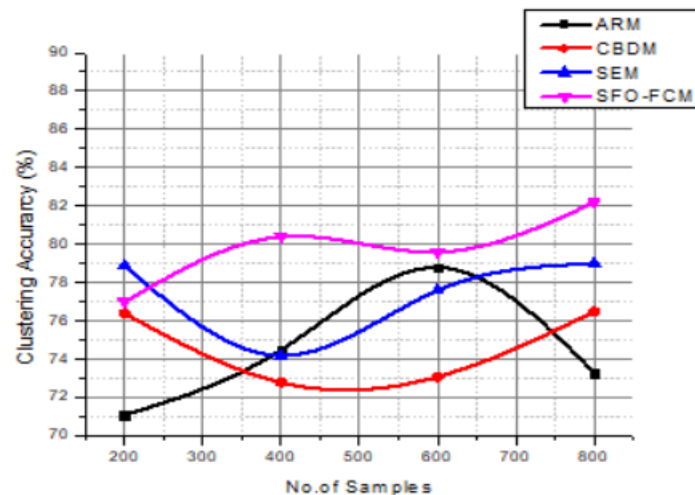


Figure 3: Clustering Accuracy

Figure 3 also juxtaposes the accuracy levels of clustering (%) at different sample sizes (200 to 800) of the four approaches, including ARM, CBDM, SEM, and SFO-FCM. SFO-FCM consistently delivers better results than others, with an accuracy range of over 78%, sometimes reaching up to 82%, demonstrating its robustness and flexibility in response to sample changes. The pattern of ARM demonstrates an initial upward trend, followed by a descent after reaching a peak of 600 samples. The measures of SEM and CBDM were moderately stable, with the latter exhibiting the worst overall performance. These findings reveal that SFO-FCM achieves better clustering accuracy in dynamic and sample-sensitive contexts.

The precision measures the proportion of identified positives that are relevant. In consumer behavior mining, it reveals the model's capability to detect significant patterns correctly while minimizing false alarms, as evaluated using equation 2. High precision in marketing means that the marketing resources are being dedicated to the right segments of customers while maintaining a focus on productivity and waste, while also avoiding false positive situations for business decisions such as providing a recommender system for unsuitable or undesirable products to a customer who is interested in finding a product or recommending segments and targeting customers who may not be looking for anything at all.

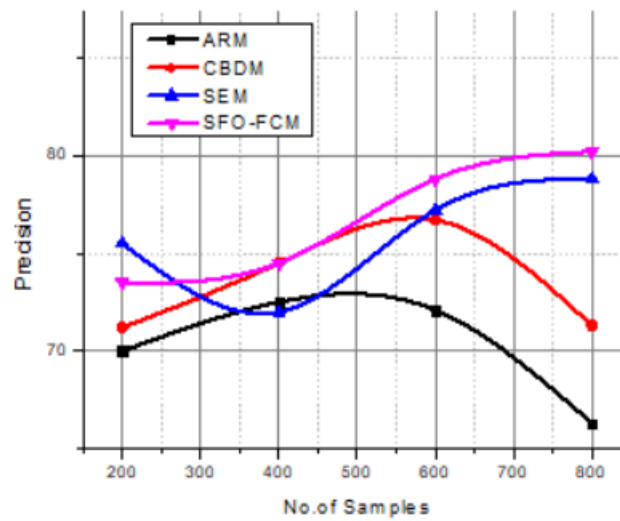


Figure 4: Precision

Figure 4 illustrates the accuracy of the four clustering methods as the sample size increases. SFO-FCM has the overall best precision rate, which rises to nearly 80%, implying greater excellence in classification. SEM continues to grow, whereas CBDM remains relatively stable. ARM performs the worst, reducing the number of samples by up to 600. SFO-FCM testifies to strong accuracy in dynamical situations.

The recall evaluates the model's ability to capture all relevant positive cases. In consumer pattern mining, high recall ensures that the system detects even infrequent or subtle behaviors, as valued using Equation 3. This is crucial in dynamic settings where identifying emerging trends or seasonal purchases can offer competitive advantages. A high recall rate ensures broader behavioral coverage, guaranteeing that no valuable consumer pattern is overlooked, and supports comprehensive segmentation, better personalization, and timely marketing strategies in fast-changing retail environments as shown in Table 2.

Table 2: Recall (sensitivity)

Method	ARM	CBDM	SEM	SFO-FCM
100	70.2	72.8	76.1	88.1
200	69.8	73.0	76.5	88.4
300	70.1	72.6	76.3	88.6
400	70.4	73.1	76.0	88.3

Table 3 shows that the F1-score comparison demonstrates that the proposed SFO-FCM is a superior score compared to ARM (0.68), CBDM (0.73), and SEM (0.76), with a score of 0.87. This represented a good trade-off between precision and recall, as validated using equation 4. Overall, it demonstrated the effectiveness of SFO_FCM in facilitating the detection of relevant and varied consumer purchase patterns while operating in dynamic environments.

Table 3: F1 Score

Method	ARM	CBDM	SEM	SFO-FCM
100	0.67	0.72	0.75	0.86
200	0.68	0.73	0.76	0.87
300	0.68	0.73	0.76	0.87
400	0.67	0.72	0.75	0.86

Table 4 shows that the execution time results suggest SFO-FCM has the overall minimum execution time, as it takes 9.1 seconds to execute the algorithm. It outperforms ARM, CBDM, and SEM, taking 12.8 seconds, 9.4 seconds, and 14.7 seconds to execute, respectively using equation 5. This level of efficiency makes SFO-FCM an effective agent when speed is crucial for real-time or large-scale applications, enabling the processing of dynamic data that reflects shifts in consumer behavior at a rapid pace while maintaining accuracy.

Table 4: Computation Time

Method	ARM	CBDM	SEM	SFO-FCM
100	12.5	10.1	14.5	9.0
200	12.8	10.4	14.7	9.1
300	13.0	10.6	14.8	9.2
400	12.6	10.3	14.6	9.0

Normalized Mutual Information (NMI) is a clustering metric that measures the similarity between estimated clusters and actual groupings. It measures the common information between the two assignments and normalizes it to pare away scale differences, providing a range (between zero and one). The higher the NMI score, the closer it is to the ground truth, implying that the clustering procedure is more accurate, as it preserves the underlying structure in the data. NMI can be beneficial when acquiring fuzzy and dynamic clustering models such as SFO-FCM.

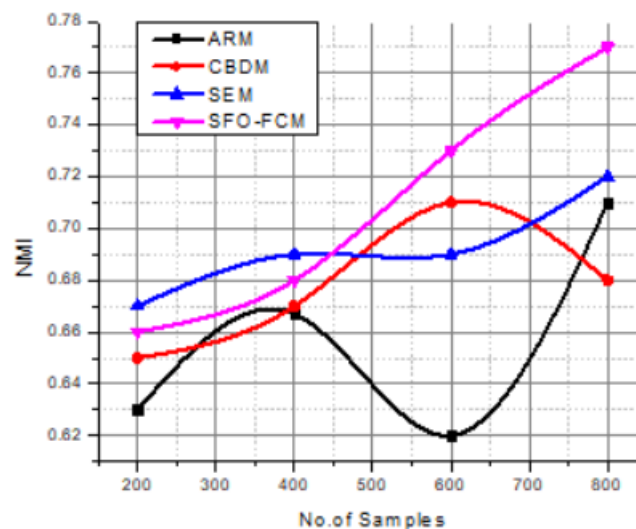


Figure 5: Analysis of NMI

Figure 5 illustrates NMI when the sample size of the four clustering methods is plotted. SFO-FCM exhibits an increasing slope and the largest NMI (~0.77), which means high cluster-label concordance. SEM increases by approximately 50 percent, with CBDM reaching its peak at 600

samples. The NMI performance of ARM is the lowest and least stable, which confirms poor clustering consistency.

The findings reveal that SFO-FCM outperforms ARM, CBDM, and SEMs on all evaluation metrics. It achieves the maximum accuracy, the best F1-score, and the minimum computational time, making it suitable for real-time clustering of evolving consumer behaviors. This establishes SFO-FCM's applicability to dynamic data-driven retail personalization and marketing optimization.

5. Conclusion

This paper introduced a new SFO-FCM methodology that leverages the ability to extract dynamic consumer purchasing behaviors. The experimental results demonstrated that the SFO-FCM methodology outperformed traditional clustering methods, including ARM, CBDM, and SEM. Clustering accuracy, F1 score, precision, recall, and computation time were all higher with SFO-FCM than with the traditional methods. Its ability to accommodate consumer behaviour that changes over time is especially beneficial for real-time retail modeling. In contrast, older segmentation models can lead to targeted marketing, enhanced customer engagement, and increased revenue. The implementation of swarm intelligence, combined with fuzzy clustering and fuzzy c-means, has surpassed traditional clustering methodologies in both processing time and segmentation types, resulting in enhanced segmentation.

For future work, it would be interesting to expand the framework by examining varying levels of deep learning-inspired sequence modeling towards increasing patterns over time. Hybrid optimization from multiple metaheuristics can improve the convergence speed and robustness of models. Furthermore, exploring applications to multilingual datasets, cross-platform consumer behavior, or integration with real-time feedback are all areas to explore for increased scalability and accuracy, enabling broader use in retail environments.

REFERENCES

- [1]. Agrahari, S., & Singh, A. K. (2022). Concept drift detection in data stream mining: A literature review. *Journal of King Saud University-Computer and Information Sciences*, 34(10), 9523-9540.
- [2]. Sato, D. M. V., De Freitas, S. C., Barddal, J. P., & Scalabrin, E. E. (2021). A survey on concept drift in process mining. *ACM Computing Surveys (CSUR)*, 54(9), 1-38.
- [3]. Fournier-Viger, P., Gan, W., Wu, Y., Nouioua, M., Song, W., Truong, T., & Duong, H. (2022, April). Pattern mining: Current challenges and opportunities. In *International Conference on Database Systems for Advanced Applications* (pp. 34-49). Cham: Springer International Publishing.
- [4]. Luo, Y., Yang, Z., Liang, Y., Zhang, X., & Xiao, H. (2022). Exploring energy-saving refrigerators through online e-commerce reviews: an augmented mining model based on machine learning methods. *Kybernetes*, 51(9), 2768-2794.
- [5]. Ernawati, E., Baharin, S. S. K., & Kasmin, F. (2021, April). A review of data mining methods in RFM-based customer segmentation. In *Journal of Physics: Conference Series* (Vol. 1869, No. 1, p. 012085). IOP Publishing.
- [6]. Selvarajan, G. P. (2021). Harnessing AI-Driven Data Mining for Predictive Insights: A Framework for Enhancing Decision-Making in Dynamic Data Environments. *International Journal of Creative Research Thoughts*, 9(2), 5476-5486.
- [7]. Santoso, M. H. (2021). Application of the association rule method using the Apriori algorithm to find sales patterns: a case study of Indomaret Tanjung Anom. *Brilliance: Research of Artificial Intelligence*, 1(2), 54-66.
- [8]. Sunarya, P. A., Rahardja, U., Chen, S. C., Lic, Y. M., & Hardini, M. (2024). Deciphering digital social dynamics: A comparative study of logistic regression and random forest in predicting e-commerce customer behavior. *Journal of Applied Data Sciences*, 5(1), 100-113.
- [9]. Abbasimehr, H., & Shabani, M. (2021). A new methodology for customer behavior analysis using time series clustering: A case study on a bank's customers. *Kybernetes*, 50(2), 221-242.

- [10]. Alves Gomes, M., & Meisen, T. (2023). A review on customer segmentation methods for personalized customer targeting in e-commerce use cases. *Information Systems and e-Business Management*, 21(3), 527-570.
- [11]. Adiputera, M. (2024). The Use of Association Rule Mining Algorithm for Consumer Purchasing Pattern Analysis in the E-commerce Industry. *Idea: Future Research*, 2(3), 89-97.
- [12]. Abbasimehr, H., & Bahrini, A. (2022). An analytical framework based on the recency, frequency, and monetary model and time series clustering techniques for dynamic segmentation. *Expert Systems with Applications*, 192, 116373.
- [13]. Ahmed, U., Srivastava, G., & Lin, J. C. W. (2022). Reliable customer analysis using federated learning and exploring deep-attention edge intelligence. *Future Generation Computer Systems*, 127, 70-79.
- [14]. Liu, X., Ding, Y., Tang, H., & Xiao, F. (2021). A data mining-based framework for the identification of daily electricity usage patterns and anomaly detection in building electricity consumption data. *Energy and Buildings*, 231, 110601.
- [15]. Ebrahimi, P., Basirat, M., Yousefi, A., Nekomahmud, M., Gholampour, A., & Fekete-Farkas, M. (2022). Social networks marketing and consumer purchase behavior: The combination of SEM and unsupervised machine learning approaches. *Big Data and Cognitive Computing*, 6(2), 35.
- [16]. Alsayat, A. (2023). Customer decision-making analysis based on big social data using machine learning: a case study of hotels in Mecca. *Neural Computing and Applications*, 35(6), 4701-4722.
- [17]. Ravinder, B., Seeni, S. K., Prabhu, V. S., Asha, P., Maniraj, S. P., & Srinivasan, C. (2024, February). Web data mining with organized contents using naive bayes algorithm. In *2024 2nd International Conference on Computer, Communication and Control (IC4)* (pp. 1-6). IEEE.
- [18]. Shu, X., & Ye, Y. (2023). Knowledge Discovery: Methods from data mining and machine learning. *Social Science Research*, 110, 102817.
- [19]. Sirichanya, C., & Kraisak, K. (2021). Semantic data mining in the information age: A systematic review. *International Journal of Intelligent Systems*, 36(8), 3880-3916.
- [20]. Czétány, L., Vámos, V., Horváth, M., Szalay, Z., Mota-Babiloni, A., Deme-Béla, Z., & Csoknyai, T. (2021). Development of electricity consumption profiles of residential buildings based on smart meter data clustering. *Energy and Buildings*, 252, 111376.
- [21]. <https://www.kaggle.com/datasets/zeesolver/consumer-behavior-and-shopping-habits-dataset>