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A Behavioral-Enhanced RFM Framework for Customer Segmentation and Churn Prediction

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Abstract Customer segmentation is a fundamental task in customer relationship management and marketing analytics. The traditional RFM (Recency, Frequency, Monetary) model is widely used; however, it does not fully capture complex behavioral patterns of customers.This paper proposes a Behavioral-Enhanced RFM (BRFM) framework that incorporates additional customer interaction features, including average quantity per order, product diversity, and purchase regularity. The framework applies feature engineering and normalization techniques, followed by K-Means clustering for customer segmentation. Clustering performance is evaluated using the Elbow method and Silhouette score.Furthermore, a predictive modeling approach is employed using machine learning algorithms to estimate customer churn. Experimental results on the Online Retail dataset indicate that, although the inclusion of behavioral features does not significantly improve clustering compactness compared to traditional RFM, it substantially enhances predictive performance. The BRFM-based model achieves higher precision, F1-score, and ROC-AUC in churn prediction.These findings demonstrate that integrating behavioral features provides a more comprehensive understanding of customer behavior and supports more effective decision-making for targeted marketing and customer retention strategies.

Keywords Customer Segmentation, RFM Model, Behavioral Features, Churn Prediction, Machine Learning, K-Means Clustering, Customer Analytics.

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1. Introduction

Customer segmentation plays a crucial role in customer relationship management and marketing analytics, enabling businesses to better understand customer behavior and design targeted marketing strategies[1]. Among various segmentation techniques, the Recency, Frequency, Monetary (RFM) model has been widely adopted due to its simplicity and effectiveness in summarizing customer transaction behavior[2, 3].

However, the traditional RFM model has notable limitations. It primarily focuses on transactional data and fails to capture deeper behavioral patterns such as customer engagement, product diversity, and purchasing regularity[4, 5]. As a result, it may not fully reflect the complexity of customer behavior in modern e-commerce environments.

To address these limitations, this study proposes a behavioral-enhanced RFM framework (BRFM), which extends the traditional RFM model by incorporating additional behavioral features. These features include average quantity per order, number of unique products purchased, and average time between purchases. By integrating these behavioral dimensions, the proposed framework aims to provide a more comprehensive representation of customer activity.

In addition to segmentation, this work integrates predictive modeling to estimate customer churn[6, 7]. Unlike many traditional approaches that focus solely on clustering, this study combines unsupervised and supervised

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learning techniques to deliver both descriptive and predictive insights. The framework employs K-Means clustering for segmentation and machine learning models for churn prediction, allowing for a more robust analysis of customer behavior.

Experimental results on the Online Retail dataset demonstrate that while the inclusion of behavioral features does not significantly improve clustering compactness, it substantially enhances predictive performance. The proposed BRFM framework achieves superior results in churn prediction compared to the traditional RFM model, highlighting the importance of incorporating behavioral features in customer analytics.

The main contributions of this paper can be summarized as follows: (1) proposing a behavioral-enhanced RFM framework, (2) integrating clustering and predictive modeling in a unified approach, and (3) demonstrating the effectiveness of behavioral features in improving churn prediction performance.

2. Related Work

2.1. Customer Segmentation

Customer segmentation is a fundamental concept in marketing and data analytics, which involves grouping customers into homogeneous segments based on shared characteristics and behavioral patterns[8, 9]. This process enables organizations to better understand customer needs, preferences, and purchasing behavior, thereby supporting more effective decision-making and personalized marketing strategies[10, 11].

Customer segmentation plays a critical role in improving customer relationship management, increasing customer retention, and maximizing business profitability. By identifying distinct customer groups, businesses can design targeted campaigns and allocate resources more efficiently[12].

2.1.1. Customer segmentation types: There are a lot of customer segmentation types[13, 14], each of them segment customers according to specific features such as :

1. Demographic segmentation: Demographic segmentation[15] segments customers based on similar characteristic like age, gender, educational level, income, and occupation,it is widely used due to the availability and simplicity of demographic data.
2. Geographic segmentation: In geographic segmentation[16, 15] we divide customers according to their geography such as location, city, country, common language, and transportation mode,this type is useful for location-based marketing strategies.
3. Psychographic segmentation: This type of segmentation is based on customer interests, value, attitude, and life style[15].
4. Technographic segmentation: This type of segmentation[16] divides customers based on the devices that customers used such as software and application,which is particularly relevant in digital and e-commerce environment.

While these segmentation approaches are effective, they often fail to fully capture dynamic customer behavior, which motivates the use of data-driven and machine learning-based techniques.

2.2. RFM Model

The RFM (Recency, Frequency, Monetary) model is one of the most widely used techniques for customer segmentation in marketing analytics. It evaluates customer value based on three key transactional dimensions[17, 18]:

- Recency (R): Measures how recently a customer has made a purchase
- Frequency (F): Represents how often a customer makes purchases
- Monetary (M): Indicates the total amount spent by the customer

The RFM model provides a simple yet effective framework for identifying valuable customers and understanding purchasing patterns. However, despite its popularity, the model has several limitations. It relies solely on historical transactional data and does not account for customer engagement, browsing behavior, or interaction patterns, which are essential for capturing modern customer dynamics in e-commerce systems[19].

These limitations highlight the need for extending the RFM model by incorporating additional behavioral features to improve segmentation accuracy and interpretability.

2.3. Extensions of RFM Models

To overcome these limitations, several studies have proposed extensions to the RFM model by incorporating additional features. One common approach is the integration of demographic attributes, resulting in RFMD models that include variables such as age, gender, and geographic location. While these extensions provide additional contextual information, demographic features are typically static and do not adequately reflect evolving customer behavior over time[20].

Other approaches have attempted to modify RFM through scoring mechanisms or weighting schemes. However, many of these methods rely on heuristic or rule-based formulations, which may introduce subjectivity and limit generalizability across different datasets.

2.4. Machine Learning for Customer Segmentation

Machine learning has become a fundamental tool in customer segmentation, enabling the identification of complex patterns in customer data that traditional methods may fail to capture. Unlike rule-based or heuristic approaches, machine learning techniques can automatically learn from data and uncover hidden structures without requiring explicit programming[21, 22].

Unsupervised learning algorithms, particularly clustering methods such as K-Means, are widely used for customer segmentation. These methods group customers based on similarities in their behavioral and transactional features, allowing businesses to identify distinct customer segments and tailor marketing strategies accordingly[23, 24].

In addition to clustering, supervised learning techniques are increasingly integrated into customer analytics to support predictive tasks such as churn prediction and customer lifetime value estimation[25]. By combining segmentation with predictive modeling, organizations can move beyond static grouping toward more dynamic and data-driven decision-making[26].

In this study, machine learning techniques are employed to enhance traditional RFM-based segmentation by incorporating behavioral features and applying clustering and predictive modeling methods. This integration enables a more comprehensive understanding of customer behavior and improves the effectiveness of targeted marketing strategies[27].

2.5. Clustering Using K-Means Algorithm

Clustering is an unsupervised learning technique that aims to group data points into homogeneous clusters based on similarity, without relying on predefined labels. It is widely used in customer segmentation to identify groups of customers with similar behavioral and transactional characteristics[28].

Among various clustering techniques, K-Means is one of the most widely used algorithms due to its simplicity and computational efficiency. The algorithm partitions a dataset into (K) clusters by minimizing the within-cluster sum of squares (WCSS), which represents the variance within each cluster[29, 30]:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} |x_i - \mu_k|^2 \tag{1}$$

where C_k denotes the set of data points assigned to cluster k, and μ_k represents the centroid of cluster k.

The K-Means algorithm operates iteratively through two main steps. First, each data point is assigned to the nearest centroid based on a distance metric, typically Euclidean distance:

$$d(x_i, \mu_k) = \sqrt{\sum_{j=1}^{n}(x_{ij} - \mu_{kj})^2} \tag{2}$$

Second, the centroids are updated by computing the mean of all data points assigned to each cluster:

$$\mu_k = \frac{1}{|C_k|}\sum_{x_i \in C_k} x_i \tag{3}$$

These steps are repeated until convergence, which occurs when cluster assignments stabilize or the reduction in the objective function becomes negligible.

In this study, K-Means clustering is applied to segment customers using both traditional RFM features and the proposed behavioral features. Prior to clustering, feature scaling is performed to ensure that all variables contribute equally to the distance calculations. The optimal number of clusters is determined using the Elbow method, and clustering performance is further evaluated using the Silhouette score[31].

2.6. Behavioral Features in Customer Analytics

Recent research has increasingly emphasized the importance of incorporating behavioral features into customer analysis. Unlike demographic attributes, behavioral variables capture dynamic aspects of customer interaction, such as purchasing diversity, basket size, and temporal purchasing patterns.

These features provide a richer and more nuanced representation of customer behavior, enabling more accurate segmentation and better understanding of customer engagement. However, the integration of behavioral features within traditional RFM-based frameworks remains relatively underexplored, particularly in a unified modeling context.

2.7. Churn Prediction and Predictive Analytics

Churn prediction is a critical application of predictive analytics in customer relationship management, aiming to identify customers who are likely to discontinue their engagement with a business. Accurate churn prediction enables organizations to implement proactive retention strategies, reduce customer loss, and improve long-term profitability[32, 33].

Machine learning techniques play a central role in churn prediction by learning patterns from historical customer data. Supervised learning algorithms, such as Random Forest, Logistic Regression, and Support Vector Machines, are commonly employed to classify customers into churn and non-churn groups. These models leverage various features, including transactional, behavioral, and temporal attributes, to capture complex customer dynamics[34].

In this study, predictive analytics is integrated with customer segmentation to enhance the effectiveness of churn prediction. The proposed BRFM framework enriches traditional RFM features with additional behavioral attributes, enabling more informative representations of customer behavior. The predictive model is trained on these features to improve classification performance.

Model performance is evaluated using standard metrics such as precision, recall, F1-score, and ROC-AUC, providing a comprehensive assessment of the model's ability to correctly identify churners while minimizing false predictions[35, 36]. This approach supports data-driven decision-making and facilitates more targeted and efficient customer retention strategies.

2.8. Research Gap and Motivation

Despite the extensive literature on RFM extensions, machine learning-based segmentation, and churn prediction, several gaps remain. First, traditional RFM models fail to capture behavioral complexity. Second, demographic-based extensions do not adequately reflect dynamic customer interactions. Third, segmentation and prediction are often addressed as separate problems rather than within a unified analytical framework.

To address these limitations, this study proposes a Behavioral-Enhanced RFM (BRFM) framework that integrates behavioral features with selected RFM variables and combines clustering with predictive modeling. This unified approach enables both descriptive segmentation and predictive analysis, providing a more comprehensive understanding of customer behavior and supporting more effective decision-making.

2.9. Contributions

This study makes the following key contributions:

- It proposes a Behavioral-Enhanced RFM (BRFM) framework that extends the traditional RFM model by incorporating additional behavioral features, including purchase regularity, product diversity, and average quantity per order, to better capture customer behavior.
- It introduces an integrated analytical approach that combines unsupervised learning (K-Means clustering) with supervised machine learning techniques for churn prediction, bridging the gap between customer segmentation and predictive analytics.
- It investigates the effectiveness of selected RFM components alongside behavioral features, providing insights into feature relevance and their impact on model performance.
- It demonstrates that while behavioral features may not significantly improve clustering compactness, they substantially enhance predictive performance, highlighting their importance in customer analytics.

3. Proposed Framework

3.1. Overview of the Proposed BRFM Framework

This study proposes a Behavioral-Enhanced RFM (BRFM) framework to improve customer segmentation and churn prediction. The framework extends the traditional RFM model by incorporating additional behavioral features that capture deeper aspects of customer activity.

As illustrated in Figure 1, the proposed framework consists of four main stages: problem definition, data preprocessing and feature engineering, customer segmentation, and churn prediction.

In the first stage, the business problem and research objectives are defined. The second stage focuses on data preprocessing and the construction of both RFM and behavioral features. In the third stage, customer segmentation is performed using K-Means clustering based on the constructed feature set. Finally, the fourth stage applies machine learning models to predict customer churn and generate actionable business insights.

This integrated approach enables both descriptive and predictive analysis, providing a more comprehensive understanding of customer behavior compared to traditional RFM-based methods.

3.2. Selection of the Baseline RFM Framework

The proposed Behavioral-Enhanced RFM (BRFM) framework is built upon the traditional RFM model, which has been widely adopted in customer segmentation because of its simplicity, interpretability, and strong practical performance in transactional retail data. The traditional RFM framework evaluates customers according to three purchasing dimensions: Recency, Frequency, and Monetary value, and has been successfully applied across numerous e-commerce and retail applications.

Rather than replacing the conventional RFM model with more complex variants, this study adopts the traditional RFM framework as the baseline segmentation model. This decision was motivated by three considerations. First, the traditional RFM model is extensively validated in both academic research and industrial practice. Second, its transparent structure allows the contribution of newly introduced behavioral variables to be evaluated independently. Third, maintaining the original RFM representation preserves interpretability while enabling a fair assessment of the additional behavioral information.

Based on this rationale, three behavioral attributes are incorporated into the baseline RFM representation: Average Quantity per Order (AQO), Product Diversity (PD), and Average Days Between Orders (ADBO). These features were selected to capture complementary aspects of customer purchasing behavior that are not represented by the original RFM variables while maintaining the simplicity and interpretability of the segmentation framework.

Stage 1: Problem Definition

Business Understanding $\rightarrow$ Define Objectives $\rightarrow$ Research Questions

$\downarrow$

Stage 2: Data Preprocessing and BRFM Construction

Data Collection $\rightarrow$ Data Cleaning $\rightarrow$ BRFM Feature Engineering

$\downarrow$

Stage 3: Clustering Process

Normalization $\rightarrow$ Elbow Method $\rightarrow$ K-Means Clustering $\rightarrow$ Cluster Validation

$\downarrow$

Stage 4: Churn Prediction and Business Insights

Machine Learning Models $\rightarrow$ Model Evaluation $\rightarrow$ Customer Insights

Figure 1. Structured Workflow of the Proposed BRFM Framework

3.3. Dataset Description

This study utilizes the Online Retail dataset, which contains transactional data from a UK-based non-store online retailer[37].The dataset consists of 541,909 transactions generated by 135,080 customers over the period from 01/12/2010 to 09/12/2011.Each record represents a single transaction and includes key attributes such as CustomerID, InvoiceDate, Quantity, UnitPrice, and StockCode.To enable customer-level analysis, the transactional data was aggregated at the customer level. This aggregation allowed the computation of RFM variables (Recency, Frequency, and Monetary) as well as additional behavioral features.The richness and scale of the dataset make it suitable for both customer segmentation and churn prediction tasks.

3.4. Stage 1: Problem Definition

The first stage focuses on defining the business problem and analytical objectives. The primary goal of this study is to enhance customer segmentation and improve churn prediction by extending the traditional RFM model.

In this context, the study aims to address the following key questions:

- How can customer behavior be more effectively represented beyond traditional RFM variables?
- Can the integration of behavioral features improve predictive performance?

This stage provides the foundation for designing the proposed BRFM framework and guides the subsequent analytical steps.

3.5. Stage 2: Data Preprocessing and Feature Engineering

In this stage, transactional data is processed and transformed into meaningful features that represent customer behavior. The feature construction process consists of two main components: traditional RFM variables and behavioral features.

3.5.1. RFM Feature Construction The traditional RFM model is used to capture customer transactional behavior through three variables:

$$R_i = T_{ref} - T_{last,i} \tag{4}$$

$$F_i = n_i \tag{5}$$

$$M_i = \sum_{j=1}^{n_i} v_{ij} \tag{6}$$

where T_{ref} represents the reference date, $T_{last,i}$ is the last purchase date of customer i, n_i is the number of transactions, and v_{ij} is the transaction value.

3.5.2. Behavioral Feature Construction To overcome the limitations of the traditional RFM framework, this study introduces three complementary behavioral features that capture aspects of customer purchasing behavior not represented by Recency, Frequency, and Monetary alone. These behavioral variables were selected because they describe purchasing intensity, product diversity, and purchasing regularity, which are widely recognized as important indicators of customer engagement, loyalty, and future purchasing behavior [38, 39].

Rather than replacing the traditional RFM variables, the proposed behavioral features complement the transactional information and provide a richer representation of customer behavior while preserving the simplicity and interpretability of the original RFM framework.

Based on this rationale, the following behavioral features are constructed at the customer level:

- **Average Quantity per Order (B_1):** measures the average number of purchased items in each transaction. Unlike purchase frequency, this feature captures purchasing intensity and reflects the customer's tendency to place larger orders.
- **Unique Products (B_2):** represents the total number of distinct products purchased by a customer. This feature measures product diversity and reflects the breadth of customer interests and engagement across different product categories.
- **Average Days Between Orders (B_3):** measures the average time interval between two consecutive purchases. This feature captures purchasing regularity and provides additional temporal information beyond the Recency metric, helping distinguish consistently active customers from irregular buyers.

Each behavioral feature is computed at the customer level and normalized using Min-Max scaling:

$$B_i^{norm} = \frac{B_i - \min(B_i)}{\max(B_i) - \min(B_i)} \tag{7}$$

For completeness, a composite behavioral score can be expressed as

$$B_{score} = \frac{1}{3}\left(B_1^{norm} + B_2^{norm} + B_3^{norm}\right) \tag{8}$$

However, in the proposed BRFM framework, the behavioral variables are not aggregated into a single score. Instead, they are retained as independent features to preserve their individual discriminative information and allow the clustering algorithm to exploit the unique contribution of each behavioral characteristic.

Consequently, the final customer representation is defined as

$$X = \{R, F, M, B_1, B_2, B_3\} \tag{9}$$

However, in this study, the behavioral features are used as independent variables rather than being aggregated into a single score. This approach preserves detailed behavioral information and enables more effective clustering.

Thus, the final feature space is defined as:

$$X = R, F, M, B_1, B_2, B_3 \tag{10}$$

A sample of the constructed BRFM feature set is presented in Table 1.
Table 1 illustrates the variability in customer behavior across both transactional (RFM) and behavioral features. Some customers exhibit high monetary value and large order sizes, while others show lower engagement levels. This variability highlights the importance of incorporating behavioral features to capture diverse customer patterns.

Table 1. Sample of Raw BRFM Features (Before Normalization)

CustomerID	R	F	M	AvgQty	UniqueProd	AvgDays
12346	326	1	77183.60	74215.00	1	0.0
12347	2	7	4310.00	13.51	103	2.0
12348	75	4	1797.24	75.52	22	9.4
12349	19	1	1757.55	8.64	73	0.0
12350	310	1	334.40	11.59	17	0.0

3.5.3. Comparison with Existing RFM Frameworks To demonstrate the novelty of the proposed Behavioral-Enhanced RFM (BRFM) framework, Table 2 compares it with representative RFM-based approaches from the literature. The traditional RFM model proposed by Fader et al. [40] relies solely on Recency, Frequency, and Monetary variables for customer value analysis. Subsequent studies have extended the RFM framework by incorporating temporal information or machine learning techniques for churn prediction. However, these approaches do not explicitly model customer purchasing behavior through dedicated behavioral features. that reflect customers' purchasing habits. The proposed BRFM framework addresses this limitation by integrating three behavioral features, namely Average Quantity per Order (AQO), Product Diversity (PD), and Average Days Between Orders (ADBO), while simultaneously supporting customer segmentation and churn prediction. As shown in Table 2, the proposed BRFM framework preserves the simplicity of the traditional RFM model while

Table 2. Comparison of the proposed BRFM framework with state-of-the-art RFM-based approaches..

Study	**R**	**F**	**M**	**Behavioral Features**	**Segmentation**	**Churn**
Fader et al. [40]	✓	✓	✓	×	✓	×
Mena et al. [41]	✓	✓	✓	Temporal RFM Features	×	✓
Arefin et al. [42]	✓	✓	✓	×	✓	✓
Proposed BRFM	✓	✓	✓	AQO, PD, ADBO	✓	✓

extending it with meaningful behavioral features. Unlike conventional RFM approaches, the proposed framework jointly performs customer segmentation and churn prediction using an enriched feature space that captures both transactional and behavioral aspects of customer purchasing behavior.

3.6. Stage 3: Customer Segmentation Using K-Means

After constructing the BRFM feature set, customer segmentation was performed using K-Means clustering. Prior to clustering, all features were normalized using Min-Max scaling to ensure that no single variable dominates the distance calculations.

The K-Means algorithm aims to partition customers into (K) clusters by minimizing the within-cluster sum of squares:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} |x_i - \mu_k|^2 \tag{11}$$

where C_k represents cluster k and μ_k is the centroid of the cluster.

3.6.1. Determination of the Optimal Number of Clusters To determine the optimal number of clusters ((K)) for both the RFM and BRFM models, a comprehensive evaluation was conducted using three widely adopted clustering validation metrics: the Within-Cluster Sum of Squares (WCSS) via the Elbow method, the Silhouette Score, and the Davies–Bouldin Index. These metrics provide complementary perspectives on clustering quality, including compactness, separation, and overall structure.

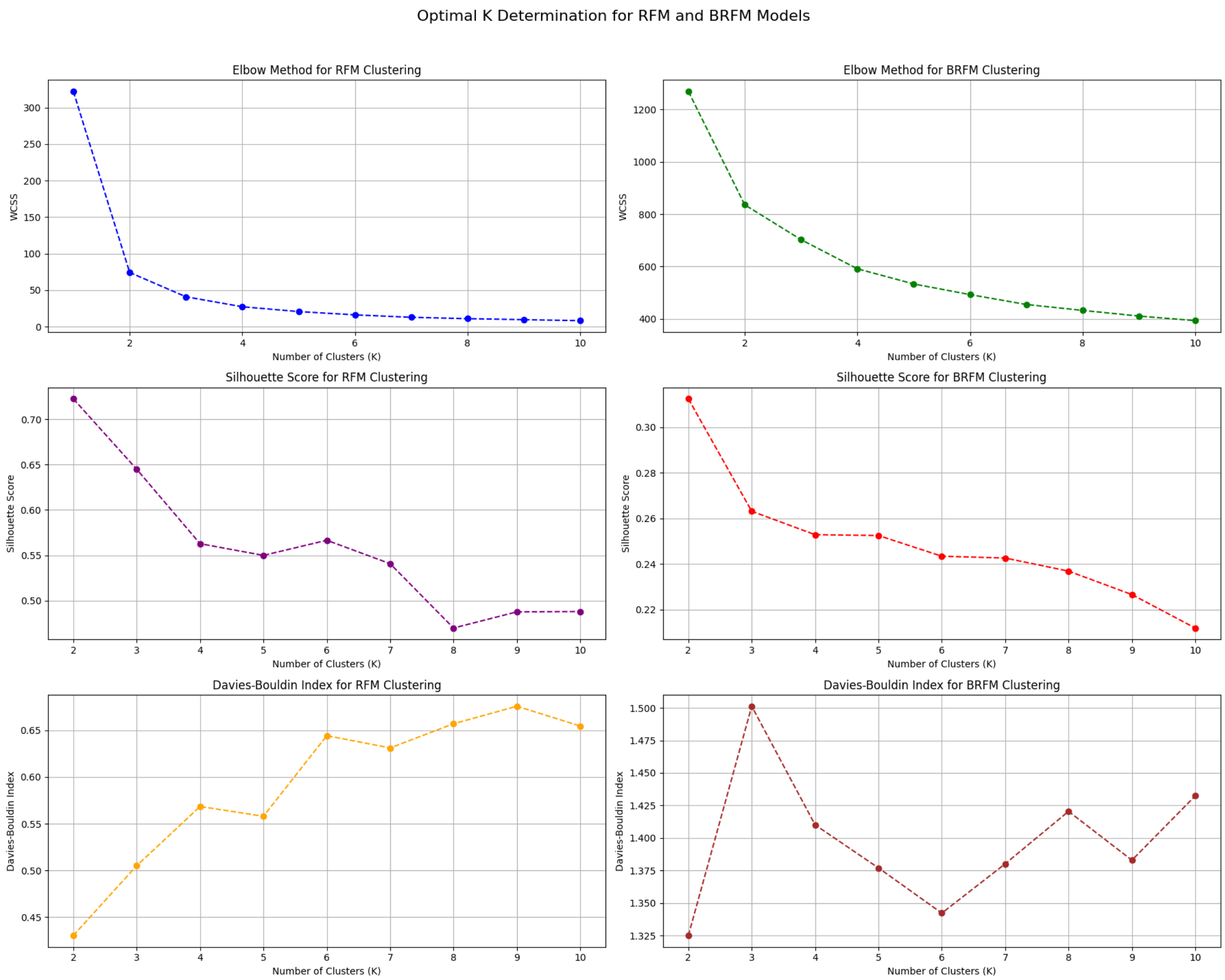

Figure 2. Evaluation of optimal number of clusters using Elbow method (WCSS), Silhouette Score, and Davies–Bouldin Index for both RFM and BRFM models.

As shown in Figure 2, the Elbow method indicates a potential optimal range between (K=3) and (K=4) for both models, where the rate of decrease in WCSS begins to stabilize, suggesting diminishing returns from increasing the number of clusters.

In contrast, the Silhouette Score reaches its maximum at (K=2) for both RFM and BRFM models, indicating that this configuration produces the most compact and well-separated clusters. Similarly, the Davies–Bouldin Index achieves its minimum value at (K=2), further confirming that smaller cluster sizes yield better statistical separation.

However, relying solely on these statistical metrics may lead to overly generalized segmentation. In practical customer analytics applications, interpretability and actionability are essential. A solution with (K=2) results in broad clusters that fail to capture meaningful distinctions between different customer behaviors.

Therefore, (K=4) was selected as a balanced choice that provides more granular and interpretable customer segments while maintaining acceptable clustering performance. This configuration enables the identification of distinct groups such as high-value customers, potential loyalists, new customers, and at-risk or churned customers.

Overall, Although both the Silhouette Score and Davies–Bouldin Index indicate that (K=2) yields the most compact and well-separated clusters, such a configuration results in overly broad segments with limited practical interpretability.In real-world customer segmentation, interpretability and actionability are critical factors.

Therefore, (K=4) was selected as a balanced choice that provides more granular and meaningful customer segments while maintaining acceptable clustering performance. This trade-off between statistical optimality and business interpretability is widely adopted in customer analytics applications.

3.6.2. Cluster Formation Following the determination of the optimal number of clusters ((K=4)), the K-Means algorithm was applied to both the RFM and BRFM feature sets to partition customers into distinct segments. Prior to clustering, all features were normalized using Min-Max scaling to ensure that variables with different scales contribute equally to the distance calculations.

K-Means initializes cluster centroids and iteratively assigns each data point to the nearest centroid based on Euclidean distance. The centroids are then updated by computing the mean of the assigned data points. This process continues until convergence is achieved, where cluster assignments stabilize and no significant changes occur in the centroid positions.

The clustering process resulted in four distinct customer segments for each model. These clusters were formed based on similarities in transactional features (Recency, Frequency, Monetary) and, in the case of the BRFM model, additional behavioral attributes such as average quantity per order, product diversity, and purchase regularity.

Compared to the traditional RFM model, the BRFM-based clustering incorporates richer behavioral information, enabling a more nuanced grouping of customers. Although the statistical compactness of clusters does not significantly improve, the inclusion of behavioral features enhances the interpretability and practical relevance of the resulting segments.

These clusters serve as the foundation for subsequent analysis, including customer profiling and churn prediction, allowing for more targeted and data-driven marketing strategies.

3.7. Predictive Model: Churn Prediction

To demonstrate the effectiveness of the proposed BRFM framework beyond clustering, a predictive model was developed to estimate customer churn.

Churn was defined based on customer inactivity using the Recency variable. A customer is considered churned if no purchase has been made within a predefined time threshold after the snapshot date.

In this study, the threshold was set to 90 days, which is commonly used in retail analytics and customer behavior studies to represent inactivity.

Thus, the churn label is defined as:

$$y_i = \begin{cases} 1 & \text{if } R_i > 90 \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

A sample of the dataset with the churn label is presented in Table 3.

Table 3. Sample of BRFM Dataset with Churn Label

CustomerID	R	F	M	AvgQty	UniqueProd	AvgDays	Churn
12346	326	1	77183.60	74215.00	1	0.0	1
12347	2	7	4310.00	13.51	103	2.0	0
12348	75	4	1797.24	75.52	22	9.4	0
12349	19	1	1757.55	8.64	73	0.0	0
12350	310	1	334.40	11.59	17	0.0	1

As shown in Table 3, customers with high Recency values (e.g., Customer 12346 and 12350) are labeled as churned, while customers with recent activity are labeled as active. This confirms that the churn definition is consistent with customer purchasing behavior.

Although Recency is used to define the churn label, it is excluded from the predictive model to avoid data leakage. Including Recency as an input feature would provide the model with direct information about the target variable, leading to misleading performance results.

3.7.1. Model Training To predict customer churn, multiple machine learning models were employed to evaluate the effectiveness of the proposed BRFM feature set. The selected models include:

- Logistic Regression (LR)
- Decision Tree (DT)
- Random Forest (RF)

These models were chosen to represent different learning paradigms, including linear models, and tree-based approaches.

The models were trained using the BRFM features, including Frequency, Monetary, and behavioral variables (AvgQuantityPerOrder, UniqueProducts, and AvgDaysBetweenOrders).

As previously discussed, the Recency feature was excluded from the training process to avoid data leakage.

3.7.2. Feature Importance Among the evaluated models, Random Forest provides an inherent measure of feature importance. Therefore, feature importance analysis was conducted using the Random Forest model.

The results are presented in Table 4.

Table 4. Feature Importance (Random Forest)

Feature	Importance
Monetary	0.273
AvgQuantityPerOrder	0.228
UniqueProducts	0.212
AvgDaysBetweenOrders	0.166
Frequency	0.121

As shown in Table 4, Monetary is the most influential feature, followed by behavioral features. The results indicate that behavioral features contribute significantly to model performance, confirming their added value beyond traditional transactional metrics.

3.8. Proposed BRFM Algorithm

To provide a clear and structured representation of the proposed BRFM framework, the overall workflow is summarized in Algorithm 1. The algorithm outlines the main steps involved in data preprocessing, feature construction, customer segmentation, and churn prediction. This representation highlights the integration of both clustering and predictive modeling within a unified pipeline.

Algorithm 1 BRFM-Based Customer Segmentation and Churn Prediction

Input: Transactional dataset D

Output: Customer segments and churn predictions

Clean and preprocess dataset D

Aggregate transactions at the customer level

Compute RFM features:

  $R_i = T_{ref} - T_{last,i}$

  $F_i = n_i$

  $M_i = \sum v_{ij}$

Compute behavioral features:

  AvgQuantityPerOrder

  UniqueProducts

  AvgDaysBetweenOrders

Normalize all features using Min-Max scaling

Apply K-Means clustering

Determine optimal K using Elbow and Silhouette methods

Define churn label:

  $y_i = 1$ if $R_i > 90$, else 0

Remove Recency feature from training set

Train machine learning models (LR, DT, RF)

Evaluate models and extract feature importance

Return: Clusters and churn predictions

The proposed algorithm ensures a systematic integration of behavioral and transactional features for improved customer analysis.

4. Results and Discussion

This section presents the experimental results of the proposed BRFM framework. The analysis includes clustering evaluation, cluster interpretation, visualization, and churn prediction performance. A comparison with the traditional RFM model is also provided to highlight the impact of incorporating behavioral features.

4.1. Clustering Evaluation: RFM vs. BRFM

To assess clustering quality, both the traditional RFM model and the proposed BRFM model were evaluated using internal validation metrics, including the Silhouette score and the Davies–Bouldin index.

For (K=4), the RFM model achieved a Silhouette score of 0.563 and a Davies–Bouldin index of 0.568. In comparison, the BRFM model achieved a Silhouette score of 0.481 and a Davies–Bouldin index of 0.672.

These results indicate that the RFM model produces slightly more compact and well-separated clusters according to internal validation metrics.

However, such metrics do not fully capture the richness of customer behavior. The BRFM model incorporates additional behavioral dimensions, enabling a more comprehensive representation of customer interactions.

4.2. Cluster Interpretation and Profiling

To better understand the customer segments identified by the BRFM model, each cluster was analyzed based on its descriptive statistics, as shown in Table 5.

- **Cluster 0 (Champions):** This segment represents high-value and highly engaged customers. It is characterized by low Recency (recent activity), high Frequency, and high Monetary value, along with strong behavioral indicators such as high average quantity per order and high product diversity. These customers contribute significantly to overall revenue.

- **Cluster 1 (Potential Loyalists):** Customers in this group exhibit moderate levels of Recency, Frequency, and Monetary value, as well as moderate behavioral engagement. They represent a stable segment with strong potential to become high-value customers.
- **Cluster 2 (New Explorers):** This segment includes recently acquired but low-value customers. It is characterized by low Frequency and Monetary value, along with limited engagement across behavioral features. These customers have not yet developed consistent purchasing behavior.
- **Cluster 3 (At-Risk/Churned):** This group represents inactive or declining customers. It is characterized by high Recency (indicating inactivity), low Frequency, low Monetary value, and weak behavioral engagement. These customers are more likely to churn.

Overall, the BRFM-based clustering provides a comprehensive segmentation by integrating transactional and behavioral attributes, enabling more effective targeting and customer retention strategies.

Table 5. Descriptive Statistics for Each BRFM Cluster (Mean Values)

Cluster	Recency	Frequency	Monetary	AvgQty	UniqueProd	AvgDays
0	19.34	6.49	3321.13	30.78	89.50	3.60
1	191.61	1.87	726.48	30.61	30.37	2.95
2	81.20	2.60	1006.06	42.32	21.54	3.80
3	308.87	1.35	565.91	21.54	21.54	0.57

4.3. *Cluster Visualization using t-SNE*

To further evaluate the clustering results, t-SNE (t-distributed Stochastic Neighbor Embedding) was applied to project the high-dimensional feature space into two dimensions for visualization[43, 44].

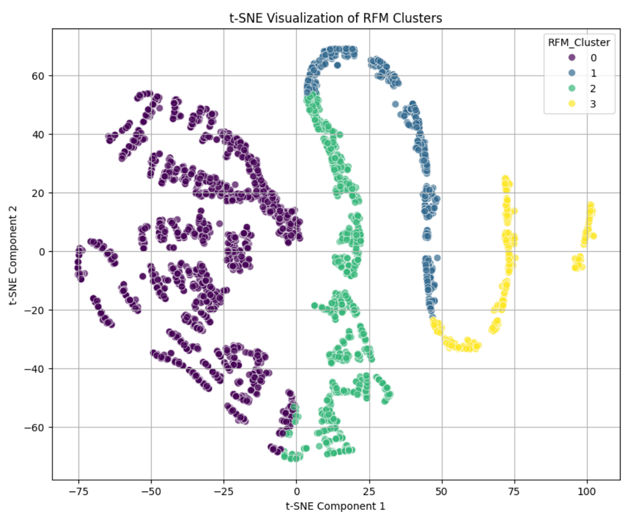

Figure 3. t-SNE Visualization of RFM Clusters

As shown in Figure 3, the clusters generated using the traditional RFM model exhibit noticeable overlap and less distinct separation between groups.

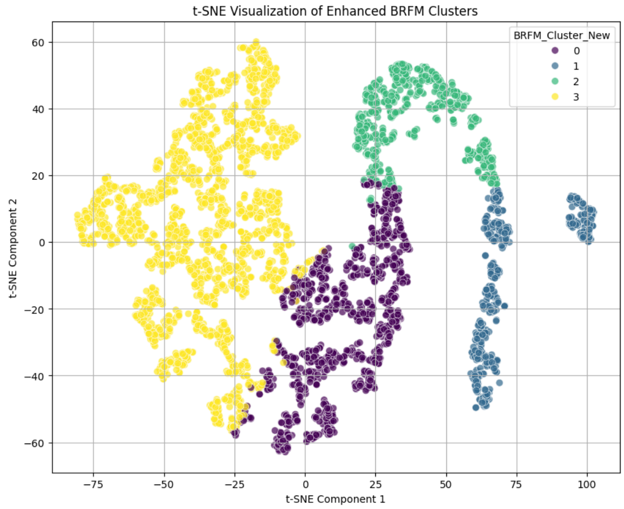

Figure 4. t-SNE Visualization of BRFM Clusters

In contrast, Figure 4 shows that the BRFM-based clustering produces more visually distinct and structured clusters compared to the traditional RFM model. However, it is important to note that t-SNE is primarily a visualization technique, and improved visual separation does not necessarily indicate better clustering performance according to quantitative metrics.

4.4. RFM-Based Churn Prediction Analysis

4.4.1. Impact of Data Leakage To investigate the effect of data leakage, an additional experiment was conducted by including the Recency feature in the predictive models.

Table 6. Model Performance with Recency Included (Data Leakage Scenario)

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest	1.000	1.000	1.000	1.000	1.000
Logistic Regression	0.998	0.993	1.000	0.997	1.000
Decision Tree	1.000	1.000	1.000	1.000	1.000

As shown in Table 6, several models achieve near-perfect performance when Recency is included. However, this result is misleading, as Recency is directly used to define the churn label. This creates a data leakage scenario where the model has direct access to the target variable.

Therefore, these results do not reflect the true predictive capability of the model.

4.4.2. RFM Model Performance without Recency To obtain a fair and realistic evaluation, the Recency feature was removed, and the models were re-trained using the remaining RFM features.

Table 7. Model Performance (RFM without Recency)

Model	Precision	Recall	F1-score	ROC-AUC
Random Forest	0.451	0.430	0.440	0.667
Logistic Regression	0.514	0.807	0.628	0.779
Decision Tree	0.440	0.437	0.438	0.578

As shown in Table 7, model performance decreases significantly after removing Recency, confirming that the previously observed near-perfect results were caused by data leakage.

Among the evaluated models, Logistic Regression achieves the best overall performance, with the highest F1-score (0.628) and ROC-AUC (0.779), indicating a strong balance between precision and recall.

4.4.3. Discussion of RFM-Based Results The results obtained from the RFM-based models highlight an important observation regarding feature selection.When Recency is included, models achieve near-perfect performance due to data leakage. However, once Recency is removed, the model performance drops significantly, providing a more realistic evaluation.This demonstrates that traditional RFM features, when properly used without leakage, provide only moderate predictive capability.In particular, even the best-performing model does not achieve high predictive performance, indicating that RFM alone may not be sufficient to fully capture customer churn behavior.This limitation motivates the need for incorporating additional behavioral features, which will be explored in the following section.

4.5. BRFM-Based Churn Prediction

4.5.1. Impact of Data Leakage Similar to the RFM model, an additional experiment was conducted by including the Recency feature in the BRFM-based models.The results showed near-perfect performance for several models, indicating the presence of data leakage. Since Recency is directly used in defining the churn label, including it as an input feature allows the model to trivially predict the target variable.Therefore, Recency was excluded from the BRFM feature set to ensure a fair and realistic evaluation.

4.5.2. Model Performance without Recency After removing the Recency feature, the models were re-trained using the BRFM features, including Frequency, Monetary, and behavioral variables.

The results are presented in Table 8.

Table 8. Model Performance (BRFM without Recency)

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest	0.717	0.596	0.478	0.531	0.785
Logistic Regression	0.687	0.520	0.855	0.646	0.794
Decision Tree	0.675	0.514	0.515	0.514	0.635

4.5.3. Discussion of BRFM Results As shown in Table 8, Logistic Regression achieves the best overall performance, with the highest F1-score (0.646) and ROC-AUC (0.794), indicating a strong balance between precision and recall.

Random Forest achieves the highest accuracy, while Decision Tree provides relatively stable but lower performance.

Compared to the RFM-based results, the BRFM model demonstrates improved predictive capability. This improvement highlights the importance of incorporating behavioral features, which capture deeper aspects of customer engagement beyond traditional transactional metrics.

These findings confirm that the BRFM framework provides a more comprehensive representation of customer behavior, leading to more effective churn prediction.

4.6. Comparison between RFM and BRFM Models

To evaluate the effectiveness of the proposed BRFM framework, a comparison was conducted between models trained using traditional RFM features and those using the extended BRFM feature set.The results indicate that incorporating behavioral features leads to improved predictive performance.Specifically, the BRFM model achieves better performance in terms of F1-score and ROC-AUC compared to the RFM-based models. This suggests that behavioral features such as average quantity per order, product diversity, and purchase regularity provide additional valuable information that is not captured by traditional RFM variables.While the RFM model provides a basic representation of customer transactions, it lacks the ability to capture deeper behavioral patterns. In contrast, the BRFM framework enhances customer representation by integrating both transactional and behavioral dimensions.This improvement is particularly evident in the ability of the model to better balance precision and recall, resulting in more reliable churn prediction.

Overall, the results demonstrate that the proposed BRFM framework offers a more robust and informative approach for customer segmentation and churn prediction compared to traditional RFM methods, confirming the added value of behavioral features in improving predictive performance.

4.7. Cohort Analysis

To gain deeper insights into customer behavior over time, a cohort analysis was conducted by grouping customers based on their first purchase month.This approach allows tracking retention and spending patterns across different customer cohorts[45]. Figure 5 reveals a consistent pattern across all cohorts: a sharp decline in retention after the first month, followed by a gradual stabilization.This indicates that a significant portion of customers make only one or two purchases before becoming inactive.However, notable differences exist between cohorts. Early cohorts, particularly 2010-12 and 2011-01, exhibit stronger long-term retention, maintaining relatively higher engagement over multiple months. In contrast, later cohorts show a faster drop in retention, suggesting a decline in customer quality or engagement over time.These findings highlight a potential shift in customer behavior, where recently acquired customers are less likely to become loyal compared to earlier cohorts.

Figure 5. Monthly Cohort Retention Rate

The Lifetime Value (LTV) analysis in Table 9 further supports this observation. Early cohorts generate significantly higher revenue compared to later cohorts, with the 2010-12 cohort achieving the highest average monetary value.

Figure 6 clearly illustrates a declining trend in customer value over time, confirming that more recent cohorts contribute less revenue.This pattern suggests that not only retention but also customer quality has

Table 9. Cohort Lifetime Value (Average Monetary)

Cohort Month	Average Monetary
2010-12	5098.47
2011-01	2699.96
2011-02	1562.83
2011-03	1424.25
2011-04	1088.74
2011-05	1604.03
2011-06	1129.98
2011-07	768.45
2011-08	1160.05
2011-09	780.26
2011-10	635.11
2011-11	470.21
2011-12	659.99

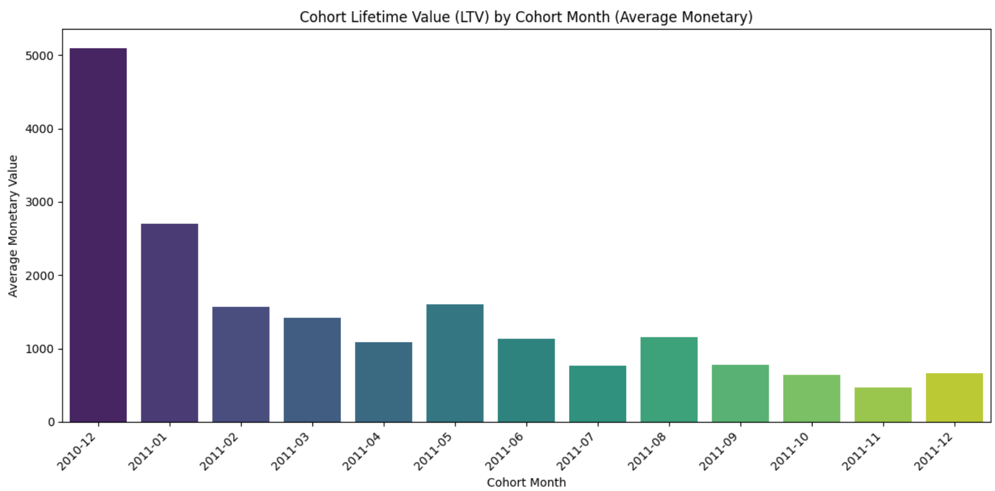

Figure 6. Cohort Lifetime Value (LTV) by Cohort Month

decreased over time, which may be attributed to changes in acquisition strategies, marketing campaigns, or customer targeting.Importantly, these temporal patterns align with the segmentation results obtained using the BRFM framework. High-value clusters identified by BRFM correspond to customers with stronger retention and higher lifetime value, while low-engagement clusters align with cohorts exhibiting rapid decline.Therefore, cohort analysis provides strong validation of the BRFM model, demonstrating that behavioral segmentation effectively captures long-term customer value and engagement dynamics.From a business perspective, these findings emphasize the need to focus on improving customer retention strategies, particularly for newly acquired cohorts, and to target high-value segments identified by the BRFM model.

4.7.1. Cohort Analysis Results The cohort retention heatmap presented in Figure 5 illustrates the month-over-month retention performance of customers grouped by their first purchase month. Each row corresponds to a cohort defined by the initial transaction period, while each column represents the proportion of customers who remained active in subsequent months. The retention values are expressed as percentages, indicating the share of customers who made repeat purchases over time.The results reveal a consistent pattern of retention decay across all cohorts. As expected in e-commerce environments, retention begins at 100% in the first month for each cohort, reflecting the initial acquisition of customers. However, a significant drop is observed immediately in the second month, indicating that a large portion of customers do not return after their first purchase. This sharp early decline highlights the challenge of converting first-time buyers into repeat customers.A deeper examination of the cohorts reveals notable differences in retention behavior. The December 2010 cohort demonstrates relatively strong retention performance, maintaining retention rates above 30% for several months and even reaching approximately 50% in later periods. This suggests that customers acquired during this period were more engaged and exhibited stronger loyalty compared to other cohorts.In contrast, several cohorts from mid to late 2011 show more rapid retention decay. For example, cohorts such as 2011-03 and 2011-04 experience retention levels dropping below 25% within the first few months. This indicates weaker engagement and a higher likelihood of early churn among customers acquired during these periods.The rate of retention decay varies significantly across cohorts, reflecting differences in customer behavior and engagement dynamics. Some cohorts exhibit gradual declines, indicating more stable customer relationships, while others show steep early drops, suggesting high churn rates shortly after acquisition. These variations may be attributed to differences in marketing strategies, seasonal effects, or changes in customer acquisition quality.It is also important to note that the presence of missing values in later periods of the heatmap is due to the limited observation window for more recent cohorts, rather than an actual absence of retention. This is a common characteristic of cohort-based analyses.

Overall, the cohort analysis provides strong evidence of customer lifecycle dynamics within the dataset. While the platform demonstrates consistent customer acquisition, maintaining long-term engagement remains a key challenge. These findings support the importance of incorporating behavioral features, as proposed in the BRFM framework, to better understand and predict customer retention and long-term value.

5. Final Comparison between the Proposed Methodology and Existing Approaches

To further validate the effectiveness of the proposed BRFM framework, a comparison is conducted with traditional and commonly used customer analysis approaches, including RFM-based models and standard machine learning techniques.Traditional RFM models rely solely on transactional features, namely Recency, Frequency, and Monetary value. While these features provide a basic understanding of customer behavior, they fail to capture deeper behavioral patterns such as purchasing diversity, order size, and temporal purchasing dynamics.In contrast, the proposed BRFM framework extends RFM by incorporating behavioral features, including average quantity per order, number of unique products, and average time between purchases. This results in a richer representation of customer behavior.From a clustering perspective, although RFM achieved slightly better internal validation metrics (e.g., Silhouette score), the BRFM model produced more interpretable and meaningful customer segments. This was confirmed through cluster profiling and visualization, where BRFM demonstrated clearer behavioral distinctions between customer groups.From a predictive perspective, BRFM outperformed traditional RFM models in terms of F1-score and ROC-AUC. This indicates that behavioral features provide additional predictive power that enhances the model's ability to identify churn patterns.Furthermore, cohort analysis provided additional validation by showing that customer segments identified using BRFM align with long-term retention and lifetime value trends. High-value clusters correspond to cohorts with higher retention and revenue, while low-engagement clusters align with declining cohorts.Compared to standard machine learning approaches that rely only on transactional features, the proposed BRFM framework offers a more comprehensive and robust solution by integrating both behavioral and transactional dimensions.

Overall, the results demonstrate that the proposed methodology provides consistent improvements in both customer segmentation and churn prediction, making it a more effective approach for customer analytics.

6. Conclusion

This paper proposed an enhanced customer analytics framework, namely BRFM, which extends the traditional RFM model by incorporating behavioral features to better capture customer purchasing patterns and engagement.The experimental results demonstrated that relying solely on traditional RFM features is insufficient for accurate churn prediction. Although RFM provides a basic representation of customer transactions, it fails to capture deeper behavioral aspects such as purchasing diversity, basket size, and temporal purchasing patterns.Furthermore, the study highlighted the critical impact of data leakage when Recency is included as a predictive feature. Models trained with Recency achieved near-perfect performance; however, these results were misleading and did not reflect true predictive capability. After removing Recency, the performance of RFM-based models dropped significantly, revealing their limited predictive power.In contrast, the proposed BRFM framework achieved improved performance by integrating behavioral features alongside transactional attributes. The results showed that BRFM provides a more balanced and reliable prediction, particularly in terms of F1-score and ROC-AUC.Additionally, clustering analysis demonstrated that BRFM enables more meaningful and interpretable customer segmentation. While traditional RFM produced slightly better internal clustering metrics, BRFM provided richer insights into customer behavior, as confirmed by cluster profiling and visualization results.Overall, the findings confirm that incorporating behavioral dimensions leads to a more comprehensive understanding of customer behavior, enhancing both segmentation and prediction tasks.Future work may explore advanced feature weighting techniques, deep learning models, and real-time customer analytics to further improve performance and scalability.

7. Limitations and Future Work

Despite the results achieved by the proposed BRFM framework, several limitations should be acknowledged:

- The dataset used in this study is limited to a single online retail platform within a specific time period, which may restrict the generalizability of the findings to other domains or industries.
- The clustering process relies on the K-Means algorithm, which assumes spherical cluster structures and may not effectively capture more complex or irregular customer patterns.
- Traditional machine learning models were employed for churn prediction. While these models demonstrate strong performance, they may not fully capture temporal dependencies and sequential patterns in customer behavior.

Future Work

Future research can further enhance the proposed BRFM framework in several directions:

- Evaluating the proposed framework on additional datasets from different industries, including subscription-based services, B2B commerce, and retail markets from different geographical regions, to further assess its robustness and generalizability.
- Investigating alternative clustering techniques, such as DBSCAN, Hierarchical Clustering, Gaussian Mixture Models (GMM), and deep clustering methods, together with comprehensive cluster stability analysis using multiple random initializations and additional cluster validation metrics.
- Exploring more advanced predictive models, including Gradient Boosting, Transformer-based architectures, and Recurrent Neural Networks (RNNs), to better capture complex customer behavioral patterns and temporal dependencies.
- Investigating adaptive churn definitions by considering different inactivity thresholds or data-driven labeling strategies, and evaluating predictive performance using additional metrics such as Precision–Recall AUC (PR-AUC) and statistical significance analysis.
- Incorporating real-time transactional data and streaming analytics to support dynamic customer segmentation and continuous churn prediction for real-world business applications.

Data availability

The dataset used in this study is publicly available from the UCI Machine Learning Repository at: https://archive.ics.uci.edu/dataset/352/online+retail.

REFERENCES

1. Miguel Alves Gomes and Tobias Meisen. 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, 2023.
2. Malay Sarkar, Aisharyja Roy Puja, and Faiaz Rahat Chowdhury. Optimizing marketing strategies with rfm method and k-means clustering-based ai customer segmentation analysis. *Journal of Business and Management Studies*, 6(2):54–60, 2024.
3. Moulay Youssef Smaili and Hanaa Hachimi. New rfm-d classification model for improving customer analysis and response prediction. *Ain Shams Engineering Journal*, 14(12):102254, 2023.
4. Wenxing Ding, Zhida Qin, Wenhao Xue, Pengzhan Zhou, and Tianyu Huang. Rfm: Refined feature modeling for multimodal recommendation. *IEEE Transactions on Consumer Electronics*, 2026.
5. Israa Lewaaelhamd. Customer segmentation using machine learning model: an application of rfm analysis. *Journal of Data Science and Intelligent Systems*, 2(1):29–36, 2024.
6. Tianyuan Zhang, Sérgio Moro, and Ricardo F Ramos. A data-driven approach to improve customer churn prediction based on telecom customer segmentation. *Future Internet*, 14(3):94, 2022.
7. Awais Manzoor, M Atif Qureshi, Etain Kidney, and Luca Longo. A review on machine learning methods for customer churn prediction and recommendations for business practitioners. *IEEE access*, 12:70434–70463, 2024.
8. Guanqun Wang. Customer segmentation in the digital marketing using a q-learning based differential evolution algorithm integrated with k-means clustering. *PloS one*, 20(2):e0318519, 2025.
9. Kemal Fiqri Handoko, Nugraha Nugraha, and Alun Sujjada. Customer segmentation-based promotion recommendation using rfm and k-means clustering on a web platform. *bit-Tech*, 8(3):3661–3672, 2026.
10. Miguel Alves Gomes and Tobias Meisen. 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, 2023.
11. Omar El Aalouche, Fayçal Messaoudi, Manal Loukili, and Riad Loukili. A temporal adaptive fuzzy clustering framework for dynamic behavioral segmentation in e-commerce. *Statistics, Optimization & Information Computing*, 15(4):3029–3041, 2026.
12. Arshi Naim. Consumer behavior in marketing patterns, types, segmentation. *European Journal of Economics, Finance and Business Development*, 1(1):1–18, 2023.
13. Pedro Quelhas Brito, Carlos Soares, Sérgio Almeida, Ana Monte, and Michel Byvoet. Customer segmentation in a large database of an online customized fashion business. *Robotics and Computer-Integrated Manufacturing*, 36:93–100, 2015.
14. Peter Kolarovszki, Jiří Tengler, and Margita Majerčáková. The new model of customer segmentation in postal enterprises. *Procedia-Social and Behavioral Sciences*, 230:121–127, 2016.
15. Daqing Chen, Sai Laing Sain, and Kun Guo. Data mining for the online retail industry: A case study of rfm model-based customer segmentation using data mining. *Journal of Database Marketing & Customer Strategy Management*, 19(3):197–208, 2012.
16. Matthias Carnein and Heike Trautmann. Customer segmentation based on transactional data using stream clustering. In *Pacific-Asia conference on knowledge discovery and data mining*, pages 280–292. Springer, 2019.
17. Sydul Arefin, Rezwanul Parvez, Tanvir Ahmed, Mostofa Ahsan, Fnu Sumaiya, Fariha Jahin, and Munjur Hasan. Retail industry analytics: Unraveling consumer behavior through rfm segmentation and machine learning. In *2024 IEEE international conference on electro information technology (eIT)*, pages 545–551. IEEE, 2024.
18. Semra Erpolat Taşabat, Tayfun Özçay, Salih Sertbaş, and Esra Akca. A new rfm model approach: Rfms. In *Industry 4.0 and the digital transformation of international business*, pages 143–172. Springer, 2023.
19. Govindaraj Ramkumar, Jayaraman Bhuvaneswari, Sujatha Venugopal, Suresh Kumar, Chandra Kala Ramasamy, and R Karthick. Enhancing customer segmentation: Rfm analysis and k-means clustering implementation. In *Hybrid and advanced technologies*, pages 70–76. CRC Press, 2025.
20. Thanh Ho, Suong Nguyen, Huong Nguyen, Ngoc Nguyen, Dac-Sang Man, and Thao-Giang Le. An extended rfm model for customer behaviour and demographic analysis in retail industry. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, 14(1):26–53, 2023.
21. Junegak Joung and Harrison Kim. Interpretable machine learning-based approach for customer segmentation for new product development from online product reviews. *International Journal of Information Management*, 70:102641, 2023.
22. Beatriz Flamia Azevedo, Ana Maria AC Rocha, and Ana I Pereira. Hybrid approaches to optimization and machine learning methods: a systematic literature review. *Machine Learning*, 113(7):4055–4097, 2024.
23. Hang Li, Lu Lin, and Huanqiang Zeng. *Machine learning methods*. Springer, 2024.
24. Koosha Sharifani and Mahyar Amini. Machine learning and deep learning: A review of methods and applications. *World Information Technology and Engineering Journal*, 10(07):3897–3904, 2023.
25. Nafez Ali and Osama Samih Shabn. Customer lifetime value (clv) insights for strategic marketing success and its impact on organizational financial performance. *Cogent Business & Management*, 11(1):2361321, 2024.
26. Kessara Kanchanapoom and Jongsawas Chongwatpol. Integrated customer lifetime value (clv) and customer migration model to improve customer segmentation. *Journal of Marketing Analytics*, 11(2):172–185, 2023.
27. Raouya El Youbi, Fayçal Messaoudi, Manal Loukili, and Mohammed El Ghazi. Elevating e-commerce customer experience: A machine learning-driven recommendation system. *Statistics, Optimization & Information Computing*, 14(2):704–717, 2025.

28. Eshan Bajal, Vipin Katara, Madhulika Bhatia, and Madhurima Hooda. A review of clustering algorithms: comparison of dbscan and k-mean with oversampling and t-sne. *Recent Patents on Engineering*, 16(2):17–31, 2022.
29. Kayalvily Tabianan, Shubashini Velu, and Vinayakumar Ravi. K-means clustering approach for intelligent customer segmentation using customer purchase behavior data. *Sustainability*, 14(12):7243, 2022.
30. Muhammad Hamka and Ngatik Ramdhoni. K-means cluster optimization for potentiality student grouping using elbow method. In *AIP Conference Proceedings*, volume 2578, page 060011. AIP Publishing LLC, 2022.
31. Ilham Firman Ashari, Eko Dwi Nugroho, Randi Baraku, Ilham Novri Yanda, and Ridho Liwardana. Analysis of elbow, silhouette, davies-bouldin, calinski-harabasz, and rand-index evaluation on k-means algorithm for classifying flood-affected areas in jakarta. *Journal of Applied Informatics and Computing*, 7(1):95–103, 2023.
32. Soumi De and P Prabu. Predicting customer churn: A systematic literature review. *Journal of Discrete Mathematical Sciences and Cryptography*, 25(7):1965–1985, 2022.
33. Meryem Houssam and Abdelilah JRAIFI. Genai meets explainability: Turning churn predictions into personalized retention strategies. *Statistics, Optimization & Information Computing*, 2026.
34. Sharmila K Wagh, Aishwarya A Andhale, Kishor S Wagh, Jayshree R Pansare, Sarita P Ambadekar, and SH Gawande. Customer churn prediction in telecom sector using machine learning techniques. *Results in Control and Optimization*, 14:100342, 2024.
35. Gireen Naidu, Tranos Zuva, and Elias Mmbongeni Sibanda. A review of evaluation metrics in machine learning algorithms. In *Computer science on-line conference*, pages 15–25. Springer, 2023.
36. Oona Rainio, Jarmo Teuho, and Riku Klén. Evaluation metrics and statistical tests for machine learning. *Scientific reports*, 14(1):6086, 2024.
37. UCI Machine Learning Repository. Online retail dataset. https://archive.ics.uci.edu/dataset/352/online+retail, 2015. Accessed: 2025-01-10.
38. Yashodhan Karulkar, Shagun Srivastava, Rakshit Nandwana, and Stacia Stanley. The growing complexity of consumer choices: Unravelling consumer patterns with k-means and fuzzy logic. *Journal of Statistical Theory and Applications*, 24(4):1165–1195, 2025.
39. Jessica Qiuhua Sheng, Da Xu, Pouyan Eslami, and Daeeun Daniel Choi. When will customers buy? a deep learning approach incorporating adaptive irregularity for next purchase prediction. *Journal of Electronic Commerce Research*, 27(4):335–350, 2026.
40. Peter S. Fader, Bruce G. S. Hardie, and Ka Lok Lee. Rfm and clv: Using iso-value curves for customer base analysis. *Journal of Marketing Research*, 42(4):415–430, 2005.
41. Gary Mena, Kristof Coussement, Koen W De Bock, Arno De Caigny, and Stefan Lessmann. Exploiting time-varying rfm measures for customer churn prediction with deep neural networks. *Annals of Operations Research*, 339(1):765–787, 2024.
42. Sydul Arefin, Rezwanul Parvez, Tanvir Ahmed, Mostofa Ahsan, Fnu Sumaiya, Fariha Jahin, and Munjur Hasan. Retail industry analytics: Unraveling consumer behavior through rfm segmentation and machine learning. In *2024 IEEE International Conference on Electro Information Technology (eIT)*, pages 545–551, 2024.
43. T Tony Cai and Rong Ma. Theoretical foundations of t-sne for visualizing high-dimensional clustered data. *Journal of Machine Learning Research*, 23(301):1–54, 2022.
44. Robert Gove, Lucas Cadalzo, Nicholas Leiby, Jedediah M Singer, and Alexander Zaitzeff. New guidance for using t-sne: Alternative defaults, hyperparameter selection automation, and comparative evaluation. *Visual Informatics*, 6(2):87–97, 2022.
45. Sushira Somavarapu and Shalu Jain. Cohort analysis for user behavior trends in marketplace platforms.