An Intelligent Customer Analytics Framework Using RFM Segmentation and Hybrid Recommendation Systems

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Abstract. Personalized recommendation systems and customer segmentation contribute significantly to enriching user experience and optimizing marketing strategies in the retail and e-commerce sectors. Traditional recommendation approaches usually suffer from issues of limited personalization and scalability. This paper presents an integrated system that combines customer segmentation based on Recency–Frequency–Monetary (RFM) analysis with customized product recommendations using content-based, collaborative, and hybrid filtering techniques. Customers are divided into four classes-Loyal Customers, Potential Loyalists, New Customers and At-Risk Customers by the implementation of K-Means clustering. Principal Component Analysis (PCA) is utilized to visualize multidimensional data and analyze the dispersion of customer behaviors across clusters. Personalized recommendations are produced by examining both product features and customer interactions, whereas the hybrid model combines these analyses to gain better accuracy and relevance. The system proposed has been implemented as an interactive Streamlit dashboard that allows real-time analysis, visualization and generation of recommendations. Empirical analysis shows that the hybrid model consistently generates more contextually appropriate recommendations than single filtering methods, demonstrating real-world usefulness for data-driven, customer-centric business approaches.

Keywords: K-Means Clustering, RFM Analysis, PCA Visualization, Hybrid Filtering.

1 Introduction

In the past few years, e-commerce websites and markets have experienced a phenomenal increase in volume. This has completely changed the way people buy anything and everything. The increase in e-commerce has given rise to a tremendous volume of data on customer search patterns, purchase counts, and spending. Beyond the money spent, businesses are now realizing the importance of data in better understanding customers and enhancing relationships with them. Existing segmentation techniques are mostly based on simple data such as age or geographic location. Such data may not necessarily reflect the actual difference. Additionally, most existing techniques, such as collaborative filtering or content-based filtering, face the same problem when data is scarce or when users are new (cold-start problem). To avoid such problems, a combination of existing techniques is used to improve results.

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The main objective of this research is to develop a methodology that uses machine learning and similarity-based techniques to establish a link between customer segmentation and product recommendations for customers. Based on the analysis using the RFM model, we were able to assess the key features associated with each transaction carried out by customers. Following that, the K-Means technique was used to segment all customers into one of the following categories: At-Risk Customers, New Customers, Potential Loyalists, and Loyal Customers. Finally, Principal Component Analysis was conducted to understand the customer segments. The recommendation system being developed uses a hybrid model that combines collaborative and content-based filtering to recommend products. The interactive dashboard being developed ensures that all information is available in a single place.

This paper's remaining sections are arranged as follows: Related research on recommendation systems and client segmentation is reviewed in Section II. The suggested methodology, which includes feature engineering, clustering, data preprocessing, and recommendation model design, is explained in Section III. The experimental findings and the suggested system's performance are covered in Section IV. Section V wraps up the report and suggests possible topics for further inquiry.

2 Related Work

Knowing what customers are looking for and offering them advice tailored to them is extremely critical to making them happy and earning more money. Old-school marketing no longer cuts it, though, because people want products produced specifically for them. Therefore, new research employs machine learning to correct this. They blend various methods for clustering people, determining their preferences, and detecting patterns. This helps companies understand who their customers are and recommend products they are most likely to purchase. By looking at the figures, companies can estimate what customers will require, get smarter about where to spend their advertising money, and bring customers back. The authors [1] discussed how the pandemic led everyone to shop online, leaving businesses playing catch-up. They developed a method to segment customers based on when they last purchased something, how frequently they purchase, and how much they spend. They then utilized this information to provide recommendations about what people had previously purchased. This assisted in marketing and allowed businesses to develop special promotions for existing and future customers.

The authors [2] conducted a study on various methods of customer grouping and found that the K-Means method, in terms of reliability and ease of implementation, was the best. It is very effective at identifying customers who are extremely valuable to your business due to their repetitive purchasing patterns. With the help of K-Means clustering, [3] also showed that customers' shopping patterns could be utilized for clustering customers who are extremely valuable for an organization in terms of revenue generated by them. Spectral clustering was proposed by K Seethalakshmi et al. [4], which could be used for increasing the accuracy of clustering customers, resulting in a better understanding of customer behavior patterns, and it was seen that this method resulted

in clustering customers that were accurate, distinct, and different from each other, thus increasing the correctness of the recommendations generated for customers.
The authors [5] also applied RFM with K-Means to segment shoppers into groups such as Loyal Customers, Potential Loyalists, At-Risk Customers, and One-Time Buyers. These assist businesses in creating precise tactics such as reward programs, thus enabling them to maximize their cash. The authors [6] comprehended this concept and applied it to hotels and created a system that approximates what individuals are going to purchase and offers them similar products, enhancing sales. Similarly, [7] discovered that whenever hotels personalized, individuals enjoyed it more and stayed longer.

The authors [8] considered Smart Product-Service Systems (Smart PSS) which utilized computers to translate language and get knowledge of user behavior in real time. This improved recommendation systems' ability to match up with what each individual desires. The authors [9] created a model that combined various approaches to discovering things that people enjoy, such as collaboration, observing popular items, and accessing sophisticated computer networks. It performed quite well at recommending the correct things, even if it was with new customers or huge amounts of data.

The authors [10] proposed incorporating a GRU-based RNN into the MyGroceryTour platform in a study related to grocery retailing. It provided weekly grocery recommendations based on store availability, prices, and past purchases using both ML and DL models. Per-user models perform better in recommendation systems than generalized approaches, which was demonstrated by the personalized GRU-based model outperforming Random Forest in accuracy.
The authors [11] provided an overview of recommendation systems that combine things. They centered their discussion on how combining multiple approaches can circumvent issues of single method usage. They also discussed issues such as handling much information and knowing what is going on around the user. [12] developed a system for online shops that classifies customers automatically with RFM, identifies significant words, clusters them with K-Means, and discovers patterns. This system transformed buying information into effective marketing concepts, indicating the significance of combining knowledge from text with clustering methods.

The authors [13] proposed one approach to create super-personal recommendations for fashion online stores. Their concept applied location information and pattern identification with RFM-grouping to recommend products according to where one is and what group one belongs to. It was better than previous approaches because it provided more precise and related outputs. They [14] also explored how models of recommendations are combining other means of getting things done, such as collaborating with one another, seeing what is contained in the product, and clustering. He also discussed issues such as being unfair with the suggestions and respecting data privacy. The authors [15] employed various forms of grouping individuals to demonstrate how it results in more targeted suggestions making individuals happier and increasing sales. The authors [16] developed a model of recommendation driven by emotion-based looking and user- and item-filtering, combined with computer learning algorithms such as Random Forest, XGBoost, and Na¨ıve Bayes.
A study was done [17], where an innovative customer analytics framework was integrated that used machine learning methods for consolidating various recommendation

systems, churn prediction, etc., into a single framework. The process of churn prediction was done by using CatBoost methods, whereas the results of recommendation were obtained by using SVD-based collaborative filtering methods, which are very accurate. The KMeans clustering methods were used for validation of customers by using Hopkins Score methods, whereas it was also used for providing a holistic approach for decision making while also keeping customers engaged with your business. In another research by [18], the researcher was primarily focused on addressing the problem of hybrid recommendation systems for the purpose of targeted marketing. The need for the comparison of the weighted, mixed, and switching methods of hybridization of recommendation systems has been emphasized. The need for the implementation of ethical personalization and XAI has been emphasized. The problem of data privacy has also been emphasized. The need for the implementation of transparency and reliability has been emphasized for the purpose of customer-based systems. They [19] have suggested that the existing problems in the recommendation systems can be solved with the help of the following three frameworks: HCC-Learn, PUPP-DA, and GSOR. The implementation of the methods of CNNs, EM soft clustering, and classification has been suggested. The presence of a large number of minority users, who are known as 'greysheep,' has improved the accuracy as well as the level of personification.

In addition to the above, [20] provided further detailed insights regarding the role played by machine learning in the creation of a personalized experience with the help of the implementation of the machine learning algorithm.

As Table 1 concludes, combining machine learning with customer clustering and hybrid recommendation systems is a solid method of achieving what consumers desire. With observation of their consumption behavior and preferences, businesses are able to receive information that enables them to make wiser, more personalized decisions. Also, combining grouping tools, RFM analysis, and blended recommendation approaches enables businesses to personalize marketing campaigns, generate interest, and keep customers satisfied. From web shops and hotels to fashion and healthcare, these hybrid approaches enable enhanced choice, new ideas, and being competitive within a world that's constantly evolving online.

Table 1. Summary of Related Research Papers

Ref.	Authors/Year	Focus /Methodology	Key Contribution
[1]	Zhao,X.;	RFM model with K-	Improved customer segmentation and personalized recommendations post-pandemic.

	Keikhosrokiani, P.; Ying, C.X.; Li, Z. (2022)	Means and association rules	
[2]	Kansal,T.; Bahuguna, S.; Singh, V.; Choudhury, T. (2018)	Compared clustering techniques on retail data	Identified K-Means as most efficient for consistent segmentation and targeting.
[3]	Tabianan, K.; Velu, S.; Ravi, V. (2022)	K-Means on shopping behavior	Segmented profitable customers to enhance loyalty and revenue.
[4]	Seethalakshmi, K.; Bhagyalakshmi,A. -2024	Advanced segmentation via KMeans and silhouette analysis	Improved e-commerce targeting using optimized cluster validation.
[5]	Syahra,Y.; Fadlil,A.; Yuliansyah, H. (2025)	RFM + K-Means for CRM in SMEs	Created data-driven loyalty programs and customer retention strategies.

[6]	Camacho, P.; de Almeida, A.; Antonio,´ N. (2020)	Customer segmentation integrated with hybrid recommendation model	Combined classification methods to predict purchase intentions; improved personalization and cross-selling.
[7]	Agabi,B.I. -2024	ML-based segmentation and recommendation for hotel retail	Developed a personalized recommendation system improving guest engagement and stay duration.
[8]	Chiu, M.C.; Huang, J.H.; Akman,G. -2021	Unsupervised NLP and DL-based recommendation in Smart PSS	Enhanced service personalization by modeling customers as co-creators of data.
[9]	Nguyen, D.N.; Nguyen, V.H.; Trinh, T.; Ho, T.; Le, H.S.	Hybrid retrieval Combining Collaborative, popularity-based, and Bayesian ranking	Improved MAP@K and MAR@K; solved cold-start and personalization challenges.

	-2024		
[10]	Chabane, N.; Bouaoune, A.;Tighilt, R.; Abdar, M. (2022)	Clustering and supervised ML algorithms (RF, DT, KNN) for shopping recommendation	Proposed hybrid supervised–unsupervised recommender achieving high accuracy on retail data.
[11]	Sabiri, B.; Khtira,A.; El Asri, B.; Rhanoui, M. -2025	Systematic review of hybrid recommender systems	Identified research gaps in hybridization, scalability, and explainability.
[12]	Shen, B. -2021	RFM + TF-IDF + K-Means with association rule mining	Built a text-enhanced segmentation and recommendation model for e-commerce.
[13]	Yıldız, E.; Şen, C.G.; Işık, E.E.	RFM and K-Means with location-based Apriori rule mining	Created a hyper-personalized fashion retail recommender improving sales.

	-2023		
[14]	Guo,Y. -2025	Collaborative, contentbased, and hybrid ML methods	Discussed applications across sectors with focus on fairness and privacy.
[15]	Gupta, S.; Israni, D. (2024)	K-Means and hierarchical clustering for segmentation	Improved marketing personalization and sales prediction.
[16]	Singh, K.; Dhawan,S.; Bali, N.; Choi, A. (2024)	Sentiment-based hybrid recommender (XGBoost, RF, NB)	Proposed ensemble hybrid achieving 96% accuracy; improved recommendation quality.
[17]	Jahan, I.; Sanam, T.F. -2024	Unified framework for churn, segmentation, and recommendation	Used CatBoost, K-Means, and SVD; enhanced retention and decision-making.

[18]	Chakraborty, S. (2025)	Hybrid recommender with weighted and mixed hybridization	Integrated Explainable AI and ethical personalization principles.
[19]	Alabdulrahman, R. (2020)	CNN + EM soft clustering for personalization	Solved sparsity and cold-start issues; boosted personalization accuracy.
[20]	Gangadharan, K.; Purandaran, A.;etal. -2025	ReviewofML-based recommendation frameworks	Highlighted trends in scalability, explainability, and business adoption.

3 Methodology

The proposed system was developed following a specific process that starts from data collection and data preparation to feature engineering, clusters, visualization, and eventually creating recommendations.

3.1 Data Collection

A synthetic retail dataset was designed to mimic real-world transactions. It comprises three integrated files: customers.csv, products.csv, and transaction.csv.

3.2 Data Preprocessing

The integration of the three data sets was carried out for the creation of a cohesive data set for transaction data. The data cleaning activities that were carried out during this phase include removing duplicate data, standardization of transaction data, handling missing data, and standardization of data type for identification data.

3.3 Feature Engineering

In order to create a numerical data set for representing the purchasing behavior of customers using RFM analysis, a numerical data set was created for each customer. It was also necessary to normalize the data for the features in a way that was suitable for analysis. This was carried out by using the MinMaxScaler method.
The features for Recency, Frequency, and Monetary for customers can be calculated as follows:

$$\textit{Type Recencyi} = \textit{Current Date} - \textit{Last Purchase Date of customer i} \tag{1}$$

$$\textit{Frequency i} = \textit{Number of Transactions by customer i} \tag{2}$$

$$\text{Monetaryi} = \sum_{j=1}^{\text{NiTransaction}} \text{Value of purchase j} \tag{3}$$

3.4 Clustering with K-Means

The normalized RFM features were clustered using K-Means with k = 4. Customers were grouped into four meaningful clusters: Loyal Customers, Potential Loyalists, New Customers, and At Risk by minimizing the within-cluster sum of squares:

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - u_j \right\|^2 \tag{4}$$

where Cj is the set of points in cluster j, xi is a customer feature vector, and μj is the centroid of cluster j, updated as:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

3.5 Visualization

Customer segments were visualized using PCA scatter plots and bar/pie charts to illustrate distribution across clusters.

3.6 Customer Insights

The system allows searching for an individual customer by ID, displaying demographic details, RFM values, assigned segment, and transaction history.
G. Recommendation System

A hybrid recommendation engine was developed:

- Content-Based Filtering: based on product features.
- Collaborative Filtering: based on customer purchase similarities.
- Hybrid Model: combines both approaches for more accurate and diverse recommendations. The Content-Based Filtering and the Collaborative Filtering are based in calculating Cosine Similarity which is computed by the formula:

$$\text{sim}(A, B) = \frac{A.B}{||A||\,||B||} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{6}$$

where A and B are vectors representing either customer purchase patterns or product feature vectors.

The hybrid recommendation combines content-based and collaborative filtering scores to produce personalized recommendations. Let P be the set of all products, and let $B_c \subset P$ be the set of products already purchased by customer c.

Content-Based Score:

For each product $p \in P$, the content-based score is computed as the average similarity to all products already purchased by the customer:

$$CB_c(p) = \frac{1}{|B_c|} \sum_{b \in B_c} \text{sim}(p, b) \tag{7}$$

where sim(p,b) is the cosine similarity between product feature vectors.

Collaborative Filtering Score:

Let U be the set of all customers and sim(c,u) be the similarity between customer c and another customer u. The collaborative filtering score for product p is:

$$F_c(p) = \sum_{u \in U, u \neq c} \text{sim}(c,u).r_u(p) \tag{8}$$

where $r_u(p)$ is 1 if customer u purchased product p, and 0 otherwise.

Hybrid Score:

The final recommendation score is a weighted combination of content-based and collaborative scores:

$$HS_c(p) = \alpha \cdot CB_c(p) + (1 - \alpha) \cdot CF_c(p), \quad 0 \leq \alpha \leq 1 \tag{9}$$

Products already purchased by the customer are excluded from the final ranking, and the top N products are recommended.

3.7 Deployment and Export

The proposed customer segmentation and hybrid recommendation system was deployed as an interactive Streamlit web application with the following features:

- Customer Insights: Any customer can be sought up using their customer ID to view their whole transaction history, RFM scores, cluster assignment, and demographic data.
- Visualization: The dashboard illustrates the general distribution of the clusters and the customer segmentation.
- Personalized Recommendations: The system employs collaborative, content-based and hybrid filtering strategies to identify products that best suit the preferences and past experiences of each individual customer.
- Export Functionality: The user can download the corresponding processed results as CSV files for additional reporting or in-depth research.

The project was a success in the conversion of an analytics-intensive process into a decision-support tool that was easily understandable, as shown in Figure 1 representing a summary of the client segmentation and recommendation system.

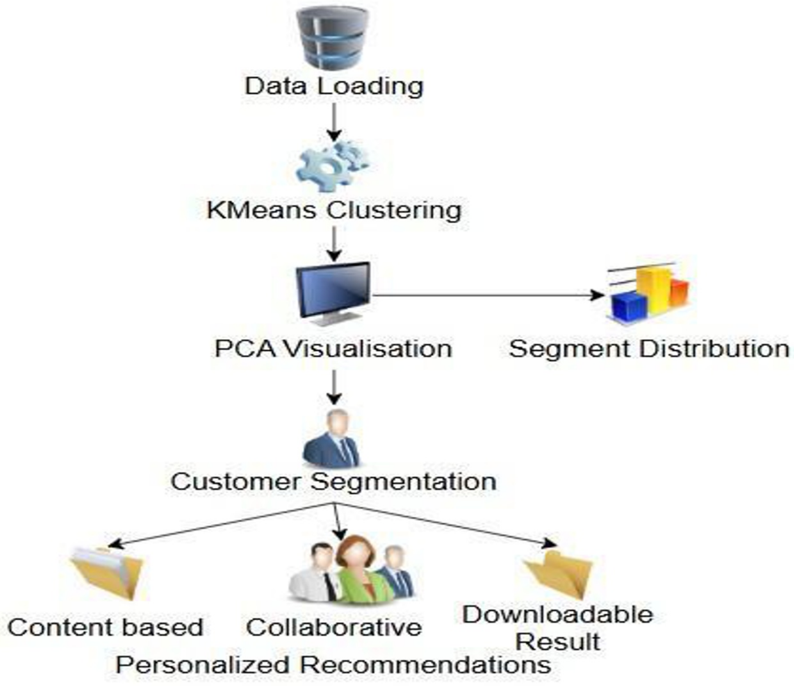

Fig. 1. System Architecture of Customer Segmentation and Recommendation Framework.

4 Results and Discussion

The results from the system were impressive and meaningful, including the clear customer classes, meaningful visualizations, and precise product recommendations.

4.1 Customer Segmentation Results

The customers were divided into four major classes based on the RFM attribute value. The classes included At-Risk Customers, New Customers, Potential Loyalists, and Loyal Customers. The results of the RFM and K-Means clustering analyses for customer segmentation are shown in Figure 2. These classes have unique patterns for customers, which help companies identify the customers who are most important or need re-engagement.

	customer_id	name	age	gender	location	Recency	Frequency	Monetary	Cluster	Segment
0	C001	Aditya Roy	38	F	Chennai	337	2	769920	3	Loyal Customers
1	C002	Sanya Chatterjee	39	F	Indore	366	2	12095	2	New Customers
2	C003	Ishaan Das	55	F	Kolkata	54	1	823440	0	Potential Loyalist
3	C004	Ira Sharma	38	F	Jaipur	548	1	5595	2	New Customers
4	C005	Riya Yadav	52	M	Trivandrum	404	3	210561	3	Loyal Customers
5	C006	Aishwarya Menon	39	F	Ahmedabad	54	2	20990	0	Potential Loyalist
6	C007	Ananya Pillai	49	F	Nagpur	333	1	1389	0	Potential Loyalist
7	C008	Aadhya Chatterjee	33	M	Chennai	695	1	34074	1	At Risk
8	C009	Riya Sharma	22	F	Hyderabad	567	2	16509	2	New Customers
9	C010	Kiara Patel	50	M	Pune	249	3	65316	3	Loyal Customers
10	C011	Sai Sharma	52	F	Lucknow	259	1	16856	0	Potential Loyalist
11	C012	Aishwarya Mukherjee	46	F	Trivandrum	82	1	564	0	Potential Loyalist
12	C013	Priya Nair	53	M	Kolkata	210	1	5910	0	Potential Loyalist
13	C014	Arjun Gupta	20	M	Chennai	1089	1	30221	1	At Risk
14	C015	Meera Sharma	58	M	Lucknow	107	2	8185	0	Potential Loyalist
15	C016	Sara Singh	38	M	Lucknow	715	2	813351	1	At Risk

Fig. 2. Customer Segmentation Output

4.2 Visualization of Segments

Figure 3: From the PCA scatter plot, it is evident that the boundaries between the clusters are distinct. This implies that the selected RFM features are efficient in characterizing the customers. The features include the distribution of the clients. This is depicted by the pie chart and the bar chart in figures 4 and 5. The graphical representation is essential in identifying the lucrative market niches. The information can be used in developing a focused marketing campaign. Furthermore, the regions where interaction can be low are identified. The revenue from these regions is also depicted.

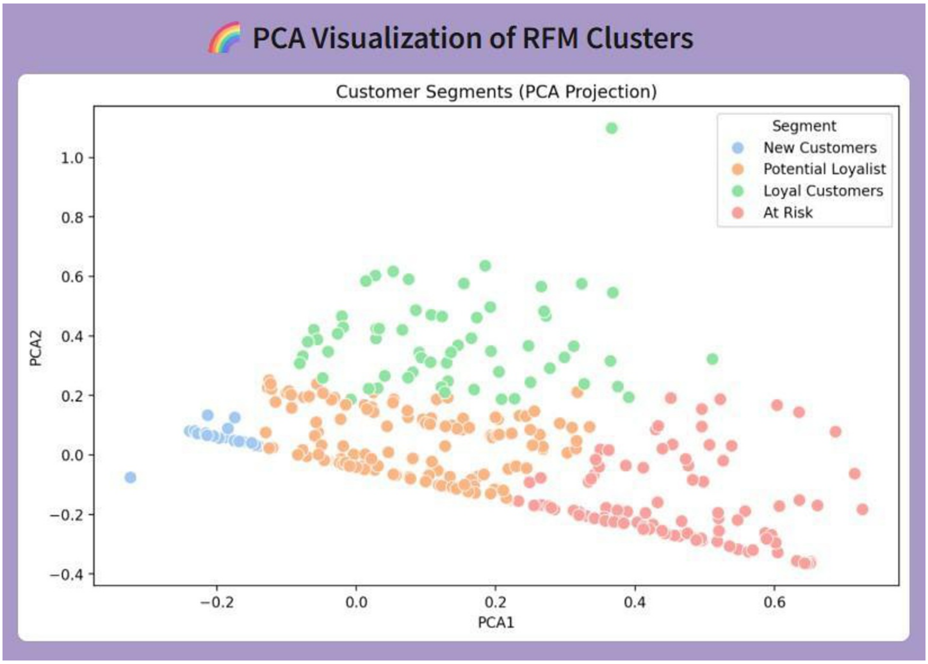

Fig. 3. Visualization of Segments.

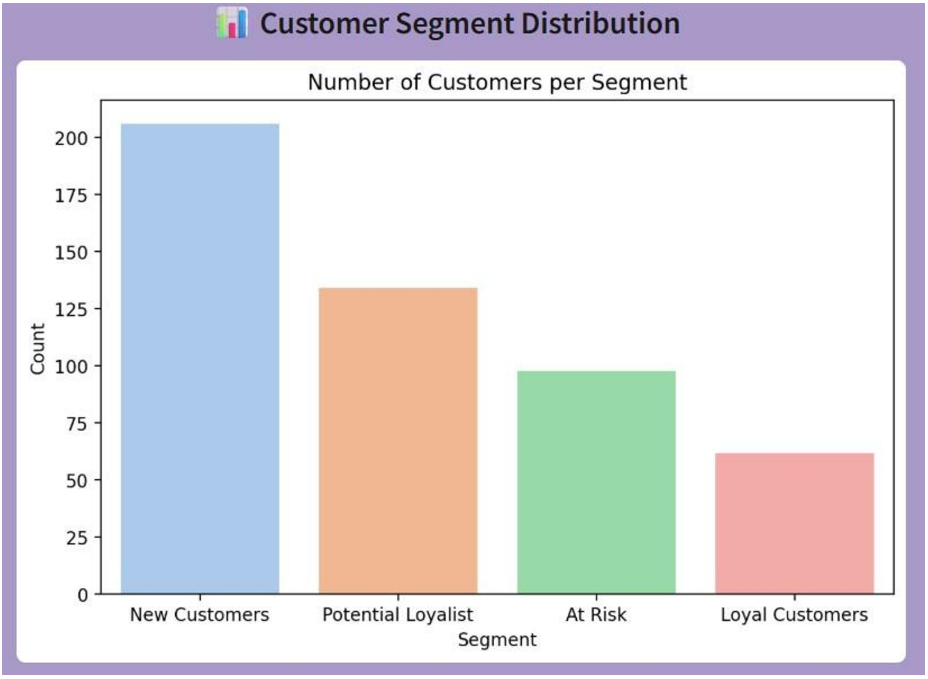

Fig. 4. Customer Segment Distribution

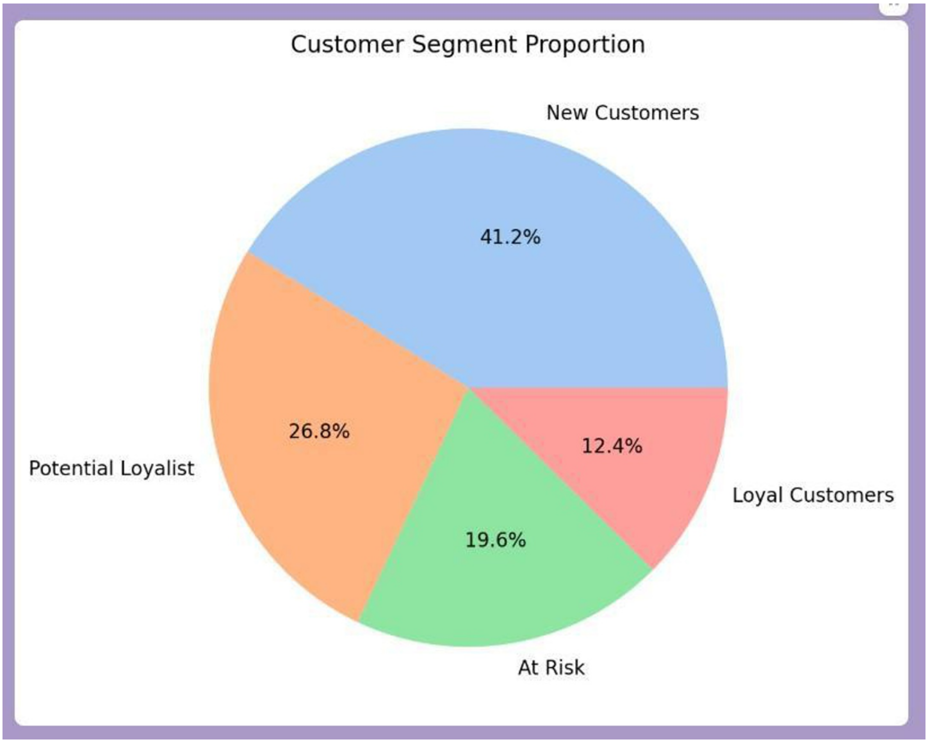

Fig. 5. Customer Segment Proportion

4.3 Customer Level Insights

The investigation of the individual customer's profile can be achieved by the use of the application dashboard. The insights that can be obtained from a focused marketing campaign can be achieved by considering the customer's demographics, transactions, and identified behaviors. Figure 6 is an illustration of a customer's profile. The information can be used in decision-making.

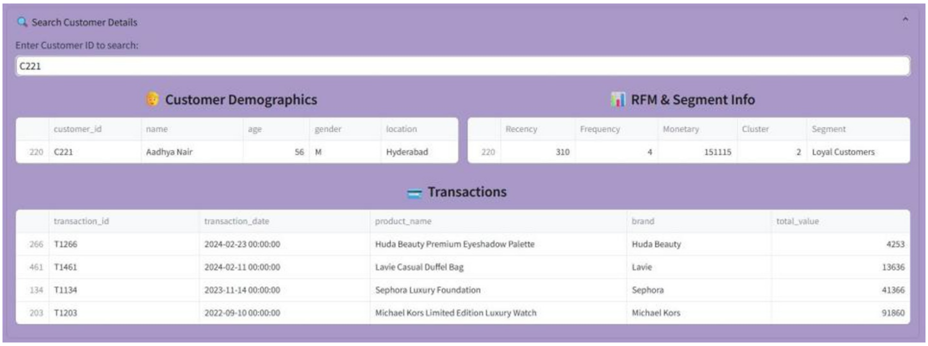

Fig. 6. Customer Details

4.4 Recommendation Performance

The hybrid model performed better than the content-based model or collaborative filtering model alone. In terms of product recommendations, the hybrid model performed better in terms of diversity and relevancy as well. While Fig. 8 shows the enhanced recommendations from the hybrid model, which combines different techniques, Fig. 7 shows a simple product recommendation using conventional collaborative filtering or content-based filtering. The enhanced recommendations from the hybrid model will result in increased consumer satisfaction, as they are more relevant and useful.

Content-Based Recommendations

	product_id	product_name	price	brand
105	127	Michael Kors Premium Handbag	29890	Michael Kors
138	168	Michael Kors Casual Handbag	32352	Michael Kors
115	141	Michael Kors Sport Tote Bag	36380	Michael Kors
154	184	Michael Kors Essential Crossbody Bag	45122	Michael Kors
200	239	Michael Kors Casual Handbag	46770	Michael Kors

Collaborative Filtering Recommendations

	product_id	product_name	price	brand
22	29	Louis Vuitton Classic T-Shirt	193393	Louis Vuitton
82	99	Nike Limited Edition Jeans	44766	Nike
88	109	Louis Vuitton Limited Edition Skirt	171051	Louis Vuitton
225	272	Estee Lauder Designer Concealer	6652	Estee Lauder
228	276	Huda Beauty Modern Mascara	3955	Huda Beauty

Fig. 7. Basic Product Recommendation

Hybrid Recommendations (Best of Both)

	product_id	product_name	price	brand
88	109	Louis Vuitton Limited Edition Skirt	171051	Louis Vuitton
105	127	Michael Kors Premium Handbag	29890	Michael Kors
138	168	Michael Kors Casual Handbag	32352	Michael Kors
115	141	Michael Kors Sport Tote Bag	36380	Michael Kors
154	184	Michael Kors Essential Crossbody Bag	45122	Michael Kors

Fig. 8. Hybrid Product Recommendation

5 Conclusion and Future Work

In this paper, a framework for customer segmentation and recommendations using RFM analysis, K-Means clustering, PCA visualization, and a hybrid model for recommendations has been discussed. The model has been implemented in an interactive environment using a Streamlit dashboard, and it may be useful in real-world applications.

In the future, deep learning-based recommenders will be integrated with the model, along with real-time data streams. The model can be implemented in a cloud environment as well.

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