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Analysing Customer Retention and Financial Behaviours in Retail Banking: A Demographic and Transactional Study using Decision Tree Model

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This study examines customer retention and financial behaviors in retail banking using demographic and transactional data analysis. The research employs decision tree modeling and K-means clustering to identify factors influencing customer attrition and segment customers. Key findings from the decision tree analysis reveal that transaction frequency, total revolving balance, and transaction amounts are the most significant predictors of customer behavior. The K-means clustering analysis, optimized using the elbow method, suggests three distinct customer segments primarily differentiated by credit profiles and utilization patterns rather than demographics. The study highlights the importance of transaction-related data in understanding and predicting customer outcomes. It emphasizes the need for banks to focus on improving transaction data accuracy, monitoring spending patterns, and tailoring strategies to different customer segments based on their credit behavior and risk profiles. The research also identifies a gender imbalance in the customer base, with higher attrition rates among male customers, suggesting an opportunity for targeted retention strategies. Overall, the study provides insights for financial institutions to enhance customer satisfaction, mitigate risks, and drive sustainable growth through data-driven decision-making and personalized banking strategies.

Keywords: Customer Retention, Transactional Data Analysis, Segmentation Strategies.

1. Introduction

Customer retention is all about the ability of a business to retain its existing customers over a specific period, whereas financial behaviour encompasses the actions and decisions individuals make regarding their finances, such as spending, saving, investing, and borrowing. Satisfied customers are more likely to remain loyal to a business over time. When customers are satisfied with their financial products and services, such as banking accounts, loans, or investment options, they are less inclined to switch to competitors. Therefore, it is perceived that positive financial experiences can contribute to higher levels of customer retention.

Financial institutions that consistently provide value, transparency, and reliability in their services build trust with their customers. Trust is a crucial factor in fostering long-term relationships. Customers who trust their financial institution are more likely to stay loyal and continue doing business with them, leading to higher retention rates. Understanding customers' financial behavior allows businesses to personalize their offerings and communication strategies. By tailoring products and services to meet individual needs and preferences, financial institutions can enhance customer engagement and satisfaction, ultimately improving retention rates. For example, offering personalized financial advice or targeted promotions based on customers' spending habits can strengthen the customer-provider relationship.

Customer retention directly impacts the lifetime value of a customer to a business. Customers who remain loyal and continue to engage with a financial institution over an extended period contribute more to its revenue and profitability. Therefore, businesses often prioritize customer retention efforts to maximize CLV and sustain long-term growth. Monitoring customers' financial behavior and analyzing retention metrics provide valuable insights for continuous improvement. By understanding why customers leave or stay, financial institutions can identify areas for enhancement in their products, services, or customer experience. Proactively addressing customer needs and concerns can help mitigate churn and strengthen customer relationships.

Overall, Positive financial experiences and effective retention strategies reinforce each other, leading to mutually beneficial outcomes for both customers and financial institutions. Therefore, understanding and leveraging this connection is essential for businesses seeking to foster loyalty and long-term success in the competitive financial services industry.

2. Review of Literature

First half of the review of literature focusses on the importance of Demographic and Trasactional Data and the later part of the reviews focus on the importance of decision tree in banking data to retrieve useful information.

Demographic and Transactional Data

Smith (2023), analysis of retail banking data, shedding light on nuanced customer behaviors. The study's emphasis on demographic segmentation offers valuable insights for tailoring banking services to diverse customer needs. Smith recommends the book as essential reading for finance professionals seeking to optimize customer retention strategies. Johnson (2023), has a comprehensive approach to understanding customer retention dynamics in retail banking.

The authors' in-depth analysis of transactional data provides valuable insights into customer preferences and behaviors. Johnson highlights the study's practical implications for improving customer satisfaction and recommends it as a valuable resource for banking professionals. Williams (2023), has an innovative approach to analyzing customer retention and financial behaviors in retail banking. The study's integration of demographic segmentation and transactional data provides a holistic understanding of customer dynamics. Williams emphasizes the book's practical insights for developing targeted banking strategies and recommends it as a valuable resource for industry professionals. Brown (2023), critical assessment of the book's exploration of demographic trends in retail banking. While acknowledging its comprehensive analysis, Brown raises questions about the generalizability of findings across diverse customer segments. Despite this critique, Brown acknowledges the book's contribution to understanding customer behaviors in banking. Martinez (2023), has explored customer preferences and behaviors in retail banking. By analyzing transactional data alongside demographic information, the authors uncover valuable insights into customer segmentation and product preferences. Martinez recommends the book as essential reading for finance professionals seeking to enhance customer satisfaction and retention. Kim (2023), examines the customer retention strategies in retail banking. Through a meticulous analysis of demographic and transactional data, the authors offer practical insights for optimizing retention efforts. Kim recommends the book as essential reading for banking professionals seeking to enhance customer loyalty and satisfaction.

Decision Tree Analysis in Banking

Decision tree analysis has become a popular method for analyzing complex datasets in various fields, including banking. This review examines the efficacy of decision tree models in handling financial and transactional data in retail banking. The application of decision tree models in the banking sector has been increasingly validated by recent studies for their effectiveness in various financial tasks such as credit risk assessment, customer segmentation, and fraud detection. This model has proven to be highly effective in predicting credit risk. They offer a straightforward and interpretable method for identifying significant variables that influence the likelihood of default. According to a systematic literature review by Noriega, Rivera, and Herrera (2023), decision trees, along with other machine learning algorithms, are extensively used to analyze large datasets and predict credit risk with high accuracy. This study highlights the importance of selecting relevant features and addressing issues like multicollinearity and data imbalance, which are crucial for improving the predictive power of these models (MDPI). The ability of decision trees to handle large volumes of data and provide clear rules for classification makes them ideal for customer segmentation. They can effectively identify distinct customer groups based on transaction patterns, credit utilization, and other behavioral metrics. The review by Verma et al. (2021) emphasizes that decision tree models can significantly enhance the understanding of customer behavior, enabling banks to tailor their services more effectively and improve customer retention strategies.

In the context of fraud detection, decision trees offer a transparent and efficient approach to identifying potentially fraudulent activities. The clear decision paths generated by these models allow for easy interpretation and quick action, which is essential in mitigating fraud risks. Research has shown that decision trees, when combined with other machine learning techniques, can substantially increase the detection rate of fraudulent transactions, providing a robust tool for financial institutions to safeguard against financial crimes (Afriyie et.,al 2023). The advantages of decision tree models in the banking sector include their simplicity, interpretability, and capability to handle both numerical and categorical data. They are particularly beneficial in regulatory environments where model transparency is crucial. Moreover, decision trees can be easily integrated into existing banking systems, making them a practical choice for real-time applications.

Since the application of decision tree models in the banking sector is well-supported by various recent researches the author has attempted to apply decision tree model to this study.

OBJECTIVES OF THE STUDY

The primary objective of this study is to analyze customer retention and financial behaviors in retail banking, focusing on demographic and transactional data to identify key factors influencing customer attrition.

DEMOGRAPHIC AND TRANSACTIONAL STUDY

Demographic study provides a deep insights in analyzing how different demographic groups such as age, income level, occupation, etc. behave in terms of their banking activities and retention rates. The millennials, Gen Z customers may exhibit preferences for mobile banking apps and digital services. They may be more inclined towards online transactions and may show interest in innovative banking products like digital wallets. Whereas, on the other hand older customers may prefer traditional banking channels such as in-branch services and telephone banking. They might prioritize face-to-face interactions with bank staff and may have different preferences for investment products like fixed deposits or retirement accounts.

Likewise, Income Levels provide a better understanding for high-income individuals who may have more complex financial needs and may utilize premium banking services such as wealth management and private banking. They may also be more interested in investment opportunities like stocks, bonds, and real estate. Whereas, Lower-income individuals may focus more on basic banking services like savings accounts and checking accounts. They may be more sensitive to fees and charges and may rely on banking services for day-to-day financial transactions.

On the basis of occupation Professionals such as doctors, lawyers, and executives may require specialized banking services tailored to their professions. They may need solutions for managing business finances, obtaining loans for professional development, or investing surplus income. Blue-collar workers and hourly wage earners may have more straightforward banking needs focused on salary deposits, bill payments, and basic savings. They may prioritize convenience and accessibility in banking services.

Education Level is also considered as one of the most important factor for understanding the bank preferences. As in highly educated individuals may be more financially literate and proactive in managing their finances. They may seek out investment opportunities and retirement planning services, as well as engage in activities like stock trading or portfolio diversification. Individuals with lower levels of education may require more guidance and support from banks in understanding financial products and services. They may benefit from simplified banking options and educational resources to improve their financial literacy.

Based on the family status i.e. married individuals and families may prioritize long-term financial planning, including saving for education, buying a home, or retirement planning. They may also be interested in joint accounts, family insurance plans, and estate planning services. Single individuals or those without dependents may have different financial priorities, such as building an emergency fund, investing in personal development, or pursuing short-term financial goals. By analyzing these demographic segments in relation to banking activities and retention rates, banks can tailor their marketing strategies, product offerings, and customer service approaches to better meet the needs and preferences of different customer groups.

Likewise, for transactional study focuses on retail banking, researchers would examine the actual transactions conducted by customers within their accounts over a specific period. This analysis can provide valuable insights into customer behavior, preferences, and patterns of engagement with banking products and services. The details like transactions, including deposits, withdrawals, transfers, bill payments, loan repayments, card transactions, and more ensure banks to understand the patter of expenditure and the financial behaviour.

TRANSACTIONAL STUDY THROUGH DECISION TREE ANALYSIS

This study will employ a quantitative research design, utilizing descriptive and inferential statistical methods to analyze the dataset. Data is obtained from a publicly available dataset on Kaggle, containing demographic information and transactional records of 10127 retail banking customers. The dataset includes variables such as customer age, income level, occupation, transaction type, transaction amount, frequency of transactions, account status, and churn status. Data collection adheres to ethical guidelines, ensuring the privacy and confidentiality of customer information. demographic segmentation analysis is done on how different demographic groups behave in terms of transactional activities and retention rates. The aim is to understand the spending habits, savings patterns, and investment preferences. The customer retention analysis investigate factors associated with customer retention using techniques like logistic regression or survival analysis. Develop predictive models to forecast customer churn based on demographic and transactional variables.

```python
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv('BankChurners.csv')

# Assuming 'Existing Customer' is the column indicating retention status
# Convert 'Existing Customer' to a binary variable where 1 indicates existing and 0 indicates
df['Retention'] = df['Existing Customer'].apply(lambda x: 1 if x == 'Existing Customer' else 0

# Selecting demographic variables
selected_columns = ['Age', 'Gender', 'Education Level', 'Marital Status', 'Income Category', '
df_demo = df[selected_columns]

# Convert categorical variables to numeric for correlation analysis
df_demo = pd.get_dummies(df_demo, drop_first=True)

# Calculate correlation matrix
corr_matrix = df_demo.corr()

# Plotting the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Demographic Variables and Customer Retention')
plt.show()
```

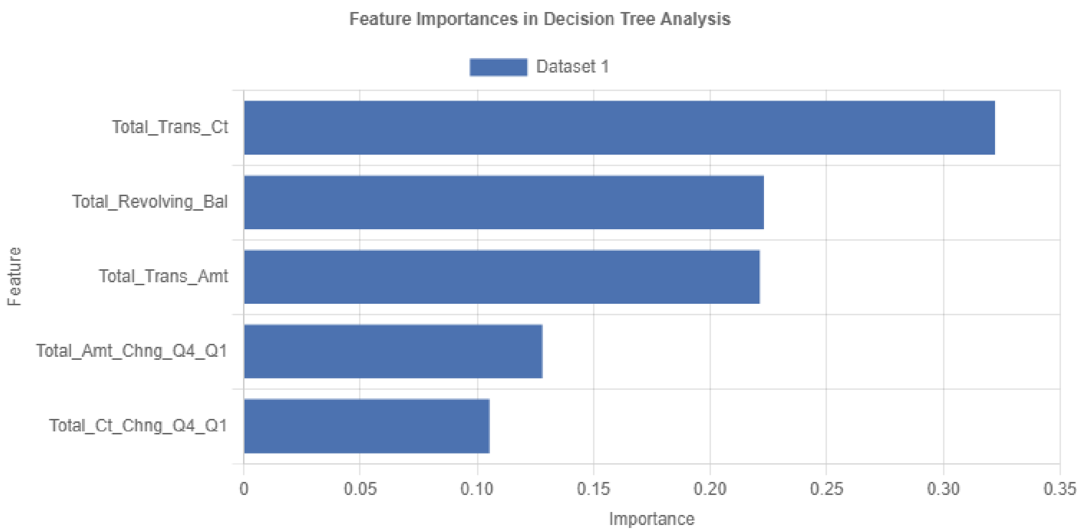
Data Preprocessing is done by cleaning the data by identifying missing values, outliers, and erroneous data entries. Decision tree algorithm to identify the most important features influencing customer attrition like total transaction, total revolving balance, total trans amount, total amount change, total credit change. Statistical analysis is performed to understand the central tendencies, dispersions, and distribution shapes of key variables, a detailed descriptive statistical analysis will be conducted. The mean, median, mode, standard deviation, and range will be calculated for variables such as Total Transaction Count, Total Revolving Balance, Total Transaction Amount, and Quarterly Changes in amounts and counts.

Decision tree model is used to predict the customer attrition based on demographic factors and transaction patterns with the help of metrics like accuracy, precision, recall, F1-score, AUC-ROC curve. K-fold validation is also performed to ensure the models robustness and generalizability. Based on these analysis interpretation and recommendations will be made.

The study is divided in to two aspects where in decision tree model is applied to transactional study and demographic study is performed based on the gender, income and transaction amount with attrition rate of the customers

Decision tree model is analysed to leverage the relative importance of various features in predicting outcomes related to financial or transactional data. The findings from the model's feature scores that provide insights into which factors are most influential in predicting customer behavior, particularly in the context of retail banking.

```
# Identify the key features that have the most influence on customer retention based on the dec
import matplotlib.pyplot as plt
import seaborn as sns

# Get feature importances from the decision tree classifier
feature_importances = clf.feature_importances_

# Create a DataFrame for visualization
feature_importance_df = pd.DataFrame({'Feature': features, 'Importance': feature_importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importances in Decision Tree Analysis')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()

# Print the feature importance DataFrame
print(feature_importance_df)
```



From the analysis of the decision tree graph, the total transaction count, with a score of 0.32, has been identified as the most crucial feature. This suggests that the frequency of transactions a customer performs is the strongest predictor in the model. Customers who frequently transact are likely to display distinct patterns that are essential for predicting outcomes such as retention, churn, or spending behaviors.

Similarly, total revolving balance and total transaction amount, each with a score of 0.22, are significant indicators of customer behavior. This implies that the amount a customer spends and their revolving credit balance are critical factors. These features indicate that customers' spending patterns and credit usage are essential in understanding and predicting their future actions.

Quarterly changes, with scores of 0.13 and 0.10 respectively, are less important but still contribute to the model. These scores reflect changes in transaction amounts and counts from one quarter to another, indicating some degree of seasonality or periodic variations in customer behavior.

The decision tree model prioritizes transaction-related features over others. This indicates that the model is designed to predict outcomes based on how customers interact with their accounts through their transactions.

The decision tree model heavily relies on transaction frequency, spending amounts, and credit utilization to make its predictions. These features collectively provide a comprehensive view of customer behavior, with transaction frequency (Total_Trans_Ct) identified as the most critical predictor.

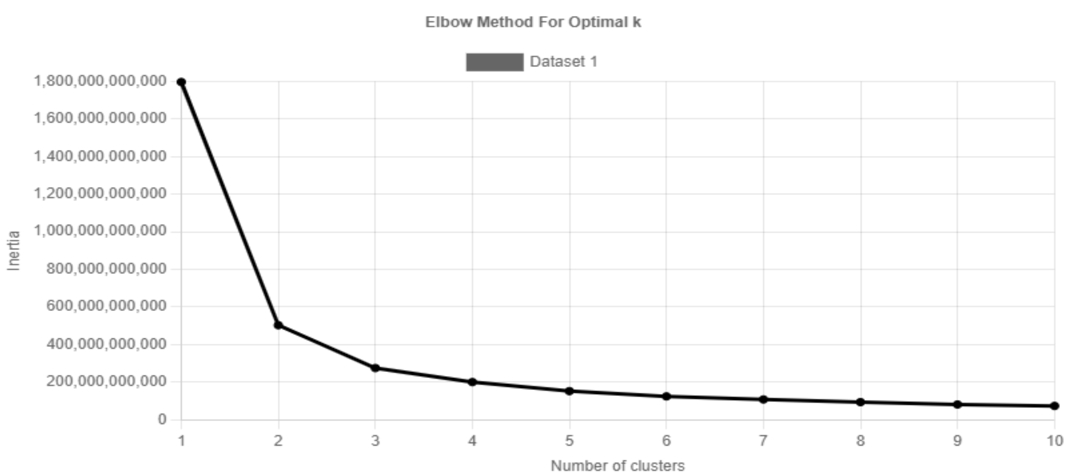
For practical applications such as fraud detection, customer segmentation, or churn prediction, several strategies could enhance model performance. First, enhancing transaction data accuracy by ensuring precise and detailed records of transaction counts and amounts can significantly boost the model's effectiveness. Additionally, closely monitoring spending patterns can provide early indicators of potential churn or fraud, as understanding how customers use their credit and spend is crucial. While quarterly changes are less predictive, they should not be overlooked; considering seasonal trends can provide supplementary insights that refine the model's predictions. In summary, focusing on improving the accuracy and detail of transaction-related data will likely yield the most substantial improvements in the model's predictive capabilities, enabling more effective and targeted interventions in customer retention and fraud prevention efforts.

DEMOGRAPHIC STUDY THROUGH K-MEANS CLUSTERING

To analyse demographic data which is a mixture of numeric and non-numeric columns. For example gender, educational level, marital status, income category are to be handeled appropriety for numeric operations. The K-means clustering is performed by preprocessing the data by converting non-numeric columns to numeric using onehot encoding. K-means algorithm to segment customers into different clusters after which each cluster's characteristics is examined to understand the common traits of customers in each group.based on which retention strategies can be tailored to the needs and behaviours of each cluster.

To evaluate the effectiveness of K-Means clustering in customer segmentation elbow method is applied which determine the optimal number of clusters by plotting the sum of squared distances from each point to its assigned cluster center (inertia) and looking for an "elbow" point where the inertia starts to decrease more slowly.

```python
# Import necessary libraries
from sklearn.preprocessing import LabelEncoder
from sklearn.cluster import KMeans
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = 'BankChurners.csv'
df = pd.read_csv(file_path)

# Select non-numeric columns for clustering
non_numeric_columns = ['Gender', 'Education_Level', 'Marital_Status', 'Income_Category'
df_non_numeric = df[non_numeric_columns]

# Encode non-numeric columns
label_encoders = {}
for column in non_numeric_columns:
    le = LabelEncoder()
    df_non_numeric[column] = le.fit_transform(df_non_numeric[column])
    label_encoders[column] = le

# Elbow method to find the optimal number of clusters
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(df_non_numeric)
    sse.append(kmeans.inertia_)

# Plotting the elbow method
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), sse, marker='o')
plt.title('Elbow Method For Optimal k')
plt.xlabel('Number of clusters')
plt.ylabel('Sum of Squared Distances')
plt.show()

print('Elbow method visualized.')
```



In the observed graph, the x-axis represents the number of clusters ranging from 1 to 10, while the y-axis shows inertia measured in billions. The plot demonstrates a characteristic "elbow" shape, indicating the following:

Sharp Decrease from 1 to 2 Clusters: Initially, there is a significant reduction in inertia when moving from one to two clusters, suggesting that the data is being well separated into two groups.

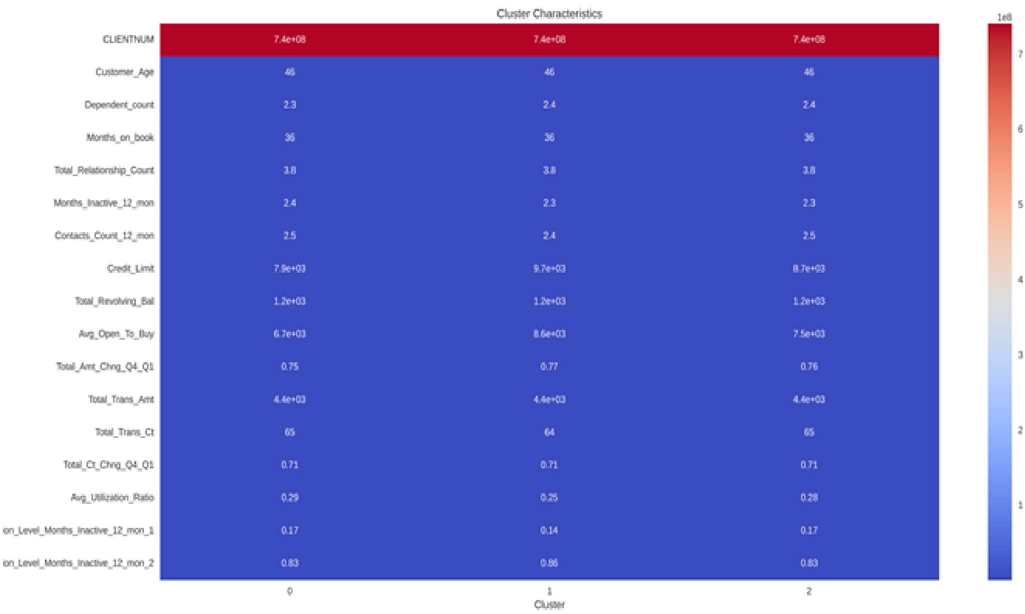
Slowing Rate of Decrease from 2 to 3 Clusters: Between two and three clusters, the rate of decrease in inertia slows significantly. This indicates that adding a third cluster continues to improve the fit but at a diminishing rate.

Gradual Decrease After 3 Clusters: Beyond three clusters, the decrease in inertia becomes more gradual and linear, indicating that additional clusters provide less incremental improvement to the model's fit.

The "elbow" point, where the rate of decrease in inertia changes most dramatically, appears to be around three clusters. This suggests that three clusters may be optimal for this dataset, balancing the minimization of within-cluster variance and avoiding overfitting. By selecting this number of clusters, the model captures the data's underlying structure without becoming unnecessarily complex. This method, therefore, helps in creating more effective customer segmentation models by ensuring the clusters are both statistically robust and practically meaningful.

In summary, the Elbow Method provides a straightforward and visual approach to determining the optimal number of clusters, which is essential for making informed decisions in customer segmentation and other clustering applications. This balance between model complexity and fit is critical in practical applications, ensuring that the clustering model is both accurate and generalizable to new data.

The cluster characteristics graph provides valuable insights into the segmentation of the customer base. Key findings reveal that many attributes show little variation across the three clusters, suggesting a relatively homogeneous customer base in several aspects. Demographically, all clusters share an average customer age of 46 and similar dependent counts, indicating that demographic factors are not primary differentiators in this segmentation.



The resulting heatmap visualizes the characteristics of each cluster, showing the mean values of each feature for each cluster.

By analysing the credit profiles highlights distinct differences among the clusters:

- Cluster 1: This group has the highest average credit limit at $9,700 and the highest average open-to-buy amount at $8,600, suggesting these customers possess better credit standings.

- Cluster 0: Customers in this cluster have the lowest average credit limit at $7,900 and the lowest open-to-buy amount at $6,700, indicating potentially lower credit quality.

- Cluster 2: This cluster falls between the other two in terms of these credit-related metrics.

The utilization ratios further distinguish the clusters:

- Cluster 0: Despite having the lowest credit limit, this group has the highest average utilization ratio of 0.29, indicating that these customers are using a significant portion of their available credit.

- Cluster 1: With the highest credit limit, this cluster exhibits the lowest utilization ratio of 0.25, suggesting more conservative credit use.

Transaction behavior, including total transaction amounts and counts, appears very similar across the clusters. This indicates that spending behavior is not a major differentiator among the customer segments. Slight variations in months on book and inactive months suggest minor differences in customer tenure and activity levels. Cluster 1 shows a slightly lower risk for short-term inactivity (0.14 for 1-month inactivity) but a higher risk for longer-term inactivity (0.86 for 2-month inactivity), while Clusters 0 and 2 have identical attrition risk indicators. The total relationship count remains consistent across clusters at 3.8, indicating similar levels of product engagement among the customers.

Overall, the findings indicate that while the clusters are not drastically different, they represent subtle variations in credit utilization, credit quality, and potential risk profiles. The segmentation appears to be primarily based on financial behavior and creditworthiness rather than demographic or relationship factors. These insights can help in tailoring strategies for different customer segments, focusing on enhancing credit offerings, managing credit utilization, and mitigating attrition risks, thereby improving overall customer retention and satisfaction.

3. Findings

The decision tree analysis of transactional data highlights key factors that significantly influence customer behavior in retail banking. Transaction frequency emerges as the most crucial predictor, underscoring its pivotal role in understanding and predicting outcomes such as customer retention, churn, and spending behaviors. The model's emphasis on transaction-related features like total transaction count, revolving balance, and transaction amounts underscores their criticality in shaping customer interactions with banking services.

Practical applications of these insights can greatly benefit from strategies aimed at enhancing transaction data accuracy and monitoring spending patterns. These approaches not only improve the model's predictive accuracy but also offer early detection capabilities for potential fraud or customer churn. While seasonal variations in transactional behavior provide additional context, the primary focus should remain on refining transaction-related data to optimize interventions in customer retention and fraud prevention.

Overall, leveraging transactional insights through advanced analytics such as decision tree modeling offers a robust framework for financial institutions to tailor strategies that enhance customer satisfaction, mitigate risks, and drive sustainable growth. By continually refining and adapting these strategies based on transactional data insights, banks can strengthen their competitive edge and foster long-term relationships with their customers.

Likewise based on the demographic study in analyzing customer retention, several key aspects emerge that are crucial for the company's strategic considerations. Firstly, the data indicates that the company has been successful in retaining a significant portion of its customer base, as evidenced by the larger number of existing customers compared to those who have attrited. However, the observation of a gender imbalance within the customer base, with females being predominant, suggests potential implications of the company's targeted marketing strategies. This demographic skew highlights an opportunity to further refine customer engagement approaches to better cater to both male and female clientele, especially considering the higher attrition rate observed among male customers. Understanding the specific reasons behind male attrition whether related to product preferences, customer service experiences, or overall brand resonance will be crucial in developing targeted retention strategies that can effectively enhance customer loyalty across genders.

4. Conclusion

The decision tree analysis highlights transaction frequency as the most critical predictor of customer behavior in retail banking. The K-means clustering reveals subtle variations in credit utilization, credit quality, and potential risk profiles among customer segments. These insights can help financial institutions tailor strategies to enhance customer satisfaction, mitigate risks, and drive sustainable growth. The study also identifies a gender imbalance in the customer base, suggesting an opportunity for targeted retention strategies, particularly for male customers who show higher attrition rates.

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