Customer Segmentation using RFM

Bank Churn Prediction

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DECLARATION

I declare that this project is my original work, completed independently, and has not been submitted for any academic assessment.

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ABSTRACT

This project investigates how integrating customer churn prediction into segmentation practices can optimize retention strategies within the Kenyan commercial banking sector. By leveraging historical account and transaction data, we develop a supervised learning model—achieving approximately 90% accuracy and an AUC of 0.90—to identify clients at high risk of attrition. Key predictive features include account tenure, balance levels, product engagement, and transaction frequency. We then apply churn-based segmentation to categorize customers into distinct cohorts (e.g., new single-product holders, fee-sensitive low-balance clients, and high-engagement loyalists). This approach reveals that early-stage and low-engagement customers are most vulnerable to leaving, while multi-product, long-tenure customers exhibit strong loyalty. By targeting high-risk segments with tailored interventions—such as fee adjustments, enhanced digital engagement, and personalized service recovery—banks can more effectively allocate resources and improve overall retention. The findings demonstrate that churn-driven segmentation not only enhances the precision of marketing efforts but also supports data-driven decision-making for sustained profitability and competitiveness in Kenya's banking industry.

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CHAPTER 1: Introduction and Background

1.1 Overview

To understand the customer in a banking environment and prevent customer churn, it is valuable to first segment the customer base by behavior. RFM analysis is a classic segmentation technique – dating back to Hughes (1994) – that does exactly this (Coşgun, 2024), (Hebbar, 2023). RFM stands for Recency, Frequency, Monetary, capturing how recently a customer transacted, how often they transact, and how much they spend. By quantifying these three dimensions from transaction data, a business can group customers into behaviorally distinct segments (Coşgun, 2024), (Hebbar, 2023). In essence, RFM "empowers businesses to segment their customer base effectively, enabling targeted marketing strategies tailored to the distinct needs and behaviours of each segment" (Coşgun, 2024). In a banking context, these metrics might be defined as days since last transaction (Recency), number of transactions or visits (Frequency), and total account balance or deposits (Monetary). The three RFM metrics are defined as follows:

1. **Recency:** How many days have passed since the customer's last purchase or transaction. A smaller recency (more recent activity) indicates a more engaged customer. For example, someone who transacted yesterday is more active than someone whose last transaction was a year ago.

2. **Frequency:** How many transactions or interactions the customer has made in a given period. Higher frequency implies strong loyalty or engagement with the bank. Frequent transactions suggest a customer is regularly using services, whereas infrequent transactions may signal waning interest

3. **Monetary:** The total value of purchases or transactions by the customer (e.g. total deposits, spending, or account balance). Customers who spend or hold more money are considered higher value. A large monetary value

indicates a high-value customer, while lower values may identify customers who could be encouraged to increase their engagement (Coşgun, 2024).

By examining these three dimensions together, RFM analysis provides a multi-faceted view of customer behavior (Coşgun, 2024). For instance, one might find a segment of customers who are very recent and frequent transactors with high monetary value (the “champions” or most valuable), versus another segment of customers who have low recency and low frequency (potential churn risks).

1.2. Problem Statement

In Kenya the majority of the banking customers are youthful, with an average age of 32 years. They spend most of their income on meeting basic needs such as food, rent and education. They have a desire to invest in their own homes through purchase of land. The sentiments from this segment are that bank products are costly, and they do not feel that the bank products are designed appropriately for them. There is an opportunity for banks to enhance the customer experience for customers by leveraging emerging technology such as artificial intelligence and machine learning to design products to meet the needs of the customers. (Mosa, 2024)

Objectives for Optimizing Customer Experience in Banking

1. To evaluate the impact of organizational integrity on customer trust and long-term banking relationships: Investigate how transparent, ethical banking practices influence customer loyalty and retention.

2. To assess the role of effective problem resolution in enhancing customer satisfaction and advocacy: Analyze how timely and empathetic handling of service failures contributes to improved customer perception (Service Recovery Paradox).

3. To examine how accurate expectation setting affects customer confidence and perceived reliability of banking services: Identify the communication strategies that best align service delivery with customer expectations.

4. To measure the effect of reducing time and effort in banking processes on customer convenience and engagement: Evaluate how streamlined digital and in-branch experiences influence customer satisfaction.

5. To investigate how personalized banking experiences impact customer connection, engagement, and product uptake: Explore the use of data-driven personalization to meet individual customer preferences and needs.

6. To understand the role of empathy in building emotionally intelligent customer interactions: Study how staff emotional responsiveness and empathetic service improve the overall emotional value of customer experiences. (Mosa, 2024)

1.3. Research Questions

This study aims to answer the following research questions:

- How can this study improve the personal experience of a customer in the banking sector?
- How can banks improve the quality of services rendered to their customers?
- Can the time and effort made by the banks in marketing be significantly improved?
- Can the efforts made by the resolutions the banking sector meet or exceed customer expectations?

1.4 Scope of the Study

This study focuses on analyzing Bank Churn metrics from Spain, Germany and France from 2020 to 2024 using a sample size of 10,000 records. This will enable us to undertake the following:

- Evaluate customer retention.
- Predict future churn logistic regression, SVM and ensemble models.

- Examine the impact of customer churn on personalization of banking products

Chapter 2: Literature Review

2.1 Introduction

Commercial banks in Kenya operate in a highly competitive market with similar products and regulated pricing. In such an environment, customer retention becomes critical to financial performance. (Mecha, Ogutu, & Ondieki, 2015) emphasize that “retaining customers is key in giving a competitive edge in the banking industry” and note that the Kenyan sector has faced growing attrition as “customers are hopping from one bank to another ”*researchgate.net*. Industry analysts likewise warn that unchecked churn erodes profitability: acquiring a new customer can cost 5–25 times more than retaining an existing onelumify360.com. Predictive analytics and churn modeling can help banks anticipate attrition, enabling proactive intervention. By identifying at-risk segments, banks can deploy targeted offers or service improvements to shore up loyalty. The goal of churn analysis is thus to stabilize revenue and extend customer lifetime value, aligning with best practices in global banking (Team Lumify, 2025)

2.2 Importance of Customer Retention

Customer retention is widely recognized as a primary driver of bank performance. Economically, retaining an existing customer is far cheaper than marketing to and onboarding a new onelumify360.com. Bain & Company famously reports acquisition costs are several times higher than retention costs, so reducing churn directly boosts profitability. In fact, research notes that sustained profitability hinges on keeping clientsresearchgate.net. (Mecha, Ogutu, & Ondieki, 2015) found that Kenyan bank managers view retention as essential for competitive advantageresearchgate.net. A stable base of loyal customers provides predictable deposits and cross-selling opportunities, smoothing revenue fluctuations. Conversely, high attrition rates compress margins and force banks into costly marketing drives to replace lost customerslumify360.comresearchgate.net. Thus, banks seek analytics that enhance lifetime value – the total revenue from a customer – by preempting the loss of revenue that churn causes.

- **Cost Savings:** As noted, retaining a customer costs a fraction of acquiring a new one (Team Lumify, 2025). By reducing churn, banks save on marketing budgets and onboarding expenses.
- **Revenue Stability:** Loyal customers contribute steady fee and interest income. Lower churn helps stabilize deposits and loan balances, supporting more reliable financial planning Bhuria et al. (2025) stress that "maintained profitability depends on keeping clients"researchgate.net, underscoring that retention is a profit protection strategy.
- **Competitive Edge:** Customer loyalty provides insulation from rivals. In Kenya's crowded banking sector, firms that can lock in customers through better relationships and service gain market share. (Mecha, Ogutu, & Ondieki, 2015) affirm that banks recognize retention as a differentiator in a slow-growth marketresearchgate.net.
- **Customer Lifetime Value:** Reducing churn lengthens each customer's tenure, increasing the cumulative revenue (lifetime value) each customer brings. Analytics-driven retention campaigns (e.g., tailored cross-sell offers) further boost value per client (Team Lumify, 2025).

2.3 Determinants of Churn in Kenyan Commercial Banks

Research on Kenyan banks highlights several key factors that influence why customers leave. Customer Relationship Management (CRM) and service stand out (Kaguri, 2016) notes that with standardized products and prices, banks must compete on relationships: "customer retention will largely be driven by customer relationship management"su-plus.strathmore.edu. In practice, managers report that weak personal relationships lead customers to migrate; one study observed that Kenyan customers "are moving from one bank to another looking for one bank that fit their needs," making it imperative for banks to cultivate close personal tiesresearchgate.net. Thus, banks with poor account management or lack of attention to client needs tend to suffer higher attrition.

Likewise, service quality and convenience are important. A survey of 403 Kenyan bank users found that branch accessibility is the top driver of satisfaction – customers value having convenient locations and 24/7 accessresearchgate.net. Conversely, high fees are the biggest source of dissatisfaction: over half of respondents cited expensive banking charges as their primary complaintresearchgate.net. These findings imply that banks with extensive branch/ATM networks and lower fees tend to retain customers better, while those with limited access or high costs risk losing them. Other related factors include service speed, digital banking usability, and error-free transactions, though these have not been individually quantified in Kenyan studies.

Product innovation also influences churn. (Mecha, Ogutu, & Ondieki, 2015) found that Kenyan banks invest heavily in product innovativeness and employee training as retention strategiesresearchgate.net. If a bank's product mix is outdated or does not meet customer needs, clients may switch to more innovative competitors. Similarly, differences in pricing (though largely regulated) and brand trust can play a role. In sectors where offerings are similar, even moderate differences in customer experience or perceived value can tip a customer toward competitorssu-plus.strathmore.eduresearchgate.net.

Summarizing, key churn drivers in Kenyan banks include:

- **Customer Relationships:** Lack of personalized service or attention prompts customers to leavesu-plus.strathmore.eduresearchgate.net.
- **Accessibility and Fees:** Limited branch/ATM coverage or high charges increase customer dissatisfactionresearchgate.net.
- **Service Quality:** Poor responsiveness, slow transactions, or unresolved complaints undermine loyalty (studies highlight that service quality is critical to retention).

- **Product and Pricing Fit:** Failure to meet changing needs (e.g. digital banking, innovative products) or adverse fee structures can push customers to competitorsresearchgate.netresearchgate.net.

2.4 Analytical Methods for Churn Prediction

To anticipate churn, banks apply a variety of data science techniques. Most churn models are supervised learning classifiers that output a churn probability or risk score. For example, Actian (n.d.) notes that a churn prediction model typically segments customers into “those likely to churn and those likely to stay” using historical labeled dataactian.com. Common algorithms include logistic regression, decision trees, and nearest-neighbor methods, but modern studies often highlight more powerful methods: ensemble and boosting models. In one recent study on banking data, researchers tested models including logistic regression, random forest, SVM and XGBoost, finding that XGBoost achieved the highest accuracy (~83%)researchgate.net. Likewise, Bhuria et al. (2025) built an ensemble (combining KNN, SVM, Random Forest, Decision Tree, XGBoost) via a voting classifier and achieved very high performance (around 90% accuracy)researchgate.netresearchgate.net. These results reflect the industry consensus that ensemble methods (random forests, gradient boosting) often outperform simpler models for churn predictionresearchgate.netresearchgate.net.

Analytic teams also emphasize feature engineering: models typically use inputs like account demographics, balances, transaction history, product usage, and service interactionsactian.com. For example, dropout risk may be predicted from declining transaction frequency, length of inactivity, or negative feedback logs. It is crucial to incorporate factors identified in Kenyan research (e.g. fee levels, branch usage) as model features.

In addition to classification models, banks use customer segmentation as part of churn analytics. This can involve clustering customers by RFM (recency, frequency, monetary value) or behavioral attributes. A segmented approach identifies high-risk groups (e.g. low-balance or seldom-active segments) and tailors models to each group. As Actian notes, one can use behavioral segmentation to group likely-churning customers by traits such as low product usage or poor service interactionactian.com. Often, churn outputs are converted into a churn risk score (e.g. 0–100) for each customeractian.com. The bank can then prioritize outreach to “high risk” segments (scores 75–100) versus “low risk” segments. Combining churn risk with customer value segmentation (high-value vs low-value customers) further refines strategy, ensuring that the bank focuses retention efforts on profitable accounts.

Overall, banks employ the following analytical approaches:

- **Supervised Classification:** Models like logistic regression, decision trees, random forest and XGBoost are trained on historical data to classify customers as churners or non-churnersresearchgate.net.
- **Ensemble Learning:** Techniques such as gradient boosting (XGBoost, LightGBM) and voting ensembles integrate multiple classifiers to boost accuracyresearchgate.netresearchgate.net.
- **Segmentation & Scoring:** Customers are grouped by risk profile or value (often using clustering or RFM analysis) and assigned churn-risk scoresactian.comactian.com.
- **Feature Engineering**: Inputs include account tenure, balance trends, product usage, fees paid, complaint history, etc., often identified via exploratory analytics or domain knowledge.
- **Time-to-Churn Models:** In some cases, survival analysis or vintage analysis track the time until a customer becomes inactive, enabling dynamic risk assessment (akin to IFC’s vintage analysis approach)documents.worldbank.orgdocuments.worldbank.org.

By integrating these methods, banks can predict churn proactively and segment the customer base for targeted retention.

2.5 Strategic Applications in Banking

Churn analytics must be translated into action to optimize operations. In practice, banks use predictive insights to tailor retention programs. For example, customers flagged as high-risk might receive personalized offers, fee waivers, or dedicated relationship managers to incentivize them to stay. One study emphasizes that predictive models “generate information that can drive proactive strategies to target at-risk customers"documents.worldbank.org. By combining model scores with customer profiles, banks can customize communications and products. Lumify360 points out that churn insights "lead to timely, relevant offers, personalized support, and more competent outreach" (Team Lumify, 2025). In essence, analytics allow a bank to engage dissatisfied or disengaged customers before they leave, rather than reactively.

Other strategic uses include revenue planning and stability. By forecasting how many customers are likely to depart, a bank can adjust its deposit and loan growth projections. Lower churn contributes to steadier deposit inflows and more predictable interest income. For example, reducing attrition of high-value customers directly preserves fee revenue from account maintenance and lending. As noted, profitability hinges on retentionresearchgate.net, so even small churn reductions can significantly improve the bottom line.

Banks also use churn insights to refine their product and pricing strategies. If analysis reveals that certain fee changes or product terminations trigger churn, the bank can reconsider those policies. The IFC found that churn modeling insights can be used to "refocus a provider's value proposition" and adjust product design or pricing to reduce. For instance, a bank might identify that younger customers are leaving due to high fees, prompting a targeted fee-reduction campaign for that demographic.

Finally, churn analytics feeds into broader customer experience improvements. Knowing which service issues most drive churn (e.g. long wait times, online banking problems) enables banks to prioritize system upgrades. It also supports loyalty programs: banks can segment loyal customers versus those likely to churn, and deploy differentiated rewards or communication strategies. In summary, data-driven churn segmentation allows Kenyan banks to personalize service, stabilize revenue streams, and align resources toward the most at-risk segments – all of which optimize operational efficiency and strategic.

2.6 Challenges in Implementation

Despite its promise, deploying churn analytics in Kenyan banks faces hurdles. Data quality and integration are major issues. Banks may have siloed legacy systems for accounts, transactions, CRM, and complaints. Consolidating these heterogeneous sources into one analytics platform is nontrivial. As industry analysts note, enterprise data “flows from many disparate sources, each in a unique or unstructured format,” making it difficult to blend and analyzenetsuite.com. Poor or missing data (e.g. incomplete address or contact info) can impair model accuracy.

Another challenge is skill and culture. Advanced analytics requires data scientists and statisticians, roles that many banks in Kenya are only beginning to develop. Even with analysts on board, integrating model outputs into front-line operations demands training and change management. Teams must learn to trust and act on predictive scores, which may conflict with traditional intuition or sales incentives. Banks also need IT infrastructure (servers, database platforms) to run machine learning, which can require significant investment.

Regulatory and ethical considerations add complexity. While Kenyan banking regulations support financial innovation, there are data privacy laws (e.g. the Data Protection Act) and capital requirements that limit how customer data can be used. Models must also avoid bias (for example, not inadvertently discriminating against small-account customers). Finally, churn events in banking are relatively rare (compared to telecom), so class imbalance can make modeling harder and require careful handling (e.g. oversampling churn cases).

Operationalizing churn analytics thus involves not only building accurate models but also integrating them into CRM systems and decision processes. Banks must define clear retention workflows (e.g. automated alerts for high-risk customers) and measure ROI. In short, data issues, talent gaps, change management, and governance concerns are significant hurdles that Kenyan banks must overcome to fully leverage predictive churn (Wingfield, 2023).

2.7 Conclusion

In summary, customer churn analysis offers Kenyan commercial banks a potent lever to optimize performance. The literature shows that focusing on retention – rather than solely on new acquisition – yields cost savings, revenue stability, and competitive advantageresearchgate.netlumify360.com. Kenyan studies (e.g. Mecha et al. 2015; Kaguri 2016) underscore that banks must understand and address churn drivers like service quality and relationship managementsu-plus.strathmore.eduresearchgate.net. Advanced analytics methods (machine learning models and segmentation) provide the means to predict which customers are at risk. When embedded in strategy, these insights enable targeted retention programs, personalized service, and dynamic pricing adjustmentslumify360.comdocuments.worldbank.org. Despite challenges in data and implementation, adopting data-driven churn management is increasingly viewed as best practice for banks. By proactively identifying churn threats and addressing them, Kenyan banks can enhance customer loyalty, stabilize earnings, and personalize service – all of which contribute to sustainable growth in the sector.

CHAPTER 3: Methodology

3.1 Introduction

We aim to accomplish the following for this study:

1. Identify and visualize which factors contribute to customer churn:

2. Build a prediction model that will perform the following:

    a. Classify if a customer is going to churn or not

    b. Preferably and based on model performance, choose a model that will attach a probability to the churn to make it easier for customer service to target low hanging fruits in their efforts to prevent churn.

3.2 Data Description and Collection

3.2.1 Source

The primary dataset for this project will be obtained from the Kaggle. The project utilizes the "Predicting Churn for Bank Customers" dataset. It contains information about 10,000 bank customers, including demographic data, account details, and whether they have exited (churned) the bank.

3.2.2 Characteristics

The project utilizes the "Predicting Churn for Bank Customers" dataset. It contains information about 10,000 bank customers, including demographic data, account details, and whether they have exited (churned) the bank.**Number of records:** 20 years of monthly data (2001–2021).

3.2.3 Attributes

• RowNumber, CustomerId, Surname: Identifiers (dropped during preprocessing).

• CreditScore: Customer's credit score.

• Geography: Customer's country of residence (France, Germany, Spain).

- Gender: Customer’s gender.
- Age: Customer’s age.
- Tenure: Number of years the customer has been with the bank.
- Balance: Account balance.
- NumOfProducts: Number of bank products (e.g., checking account, savings account) the customer has.
- HasCrCard: Whether the customer has a credit card (1=Yes, 0=No).
- IsActiveMember: Whether the customer is an active member (1=Yes, 0=No).
- EstimatedSalary: Estimated salary of the customer.
- Exited: Target variable - whether the customer churned (1=Yes, 0=No).

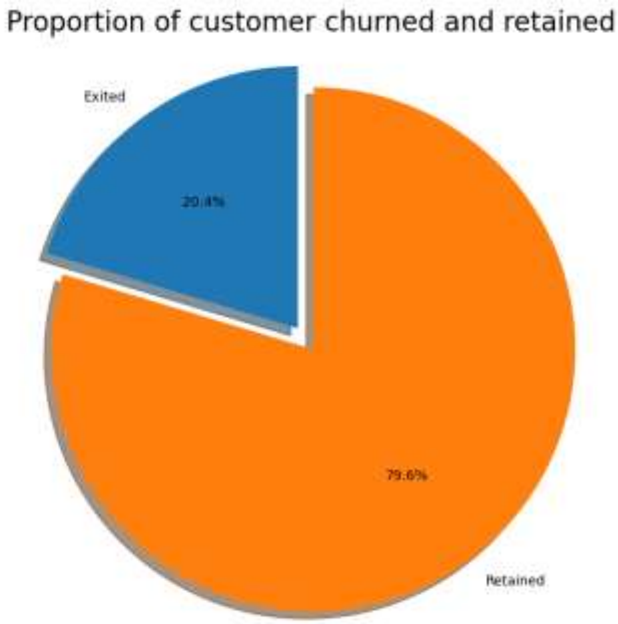
The dataset was found to have no missing values initially, which is a positive finding.

3.3 Exploratory Data Analysis

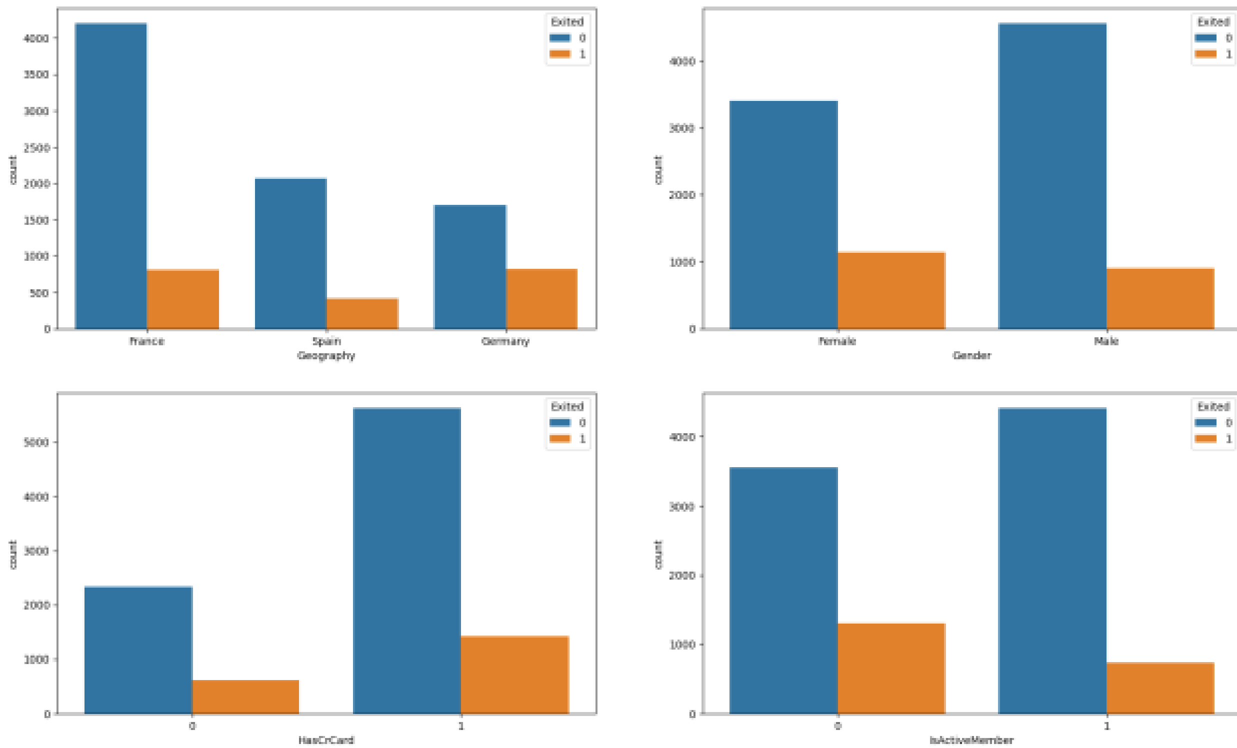
The EDA phase aimed to understand the relationships between the features and the target variable (Exited). Key findings include:

Churn Proportion

Approximately 20% of the customers in the dataset have churned, indicating an imbalanced dataset. The modeling approach needs to consider this imbalance, focusing on the ‘Churned’ class.

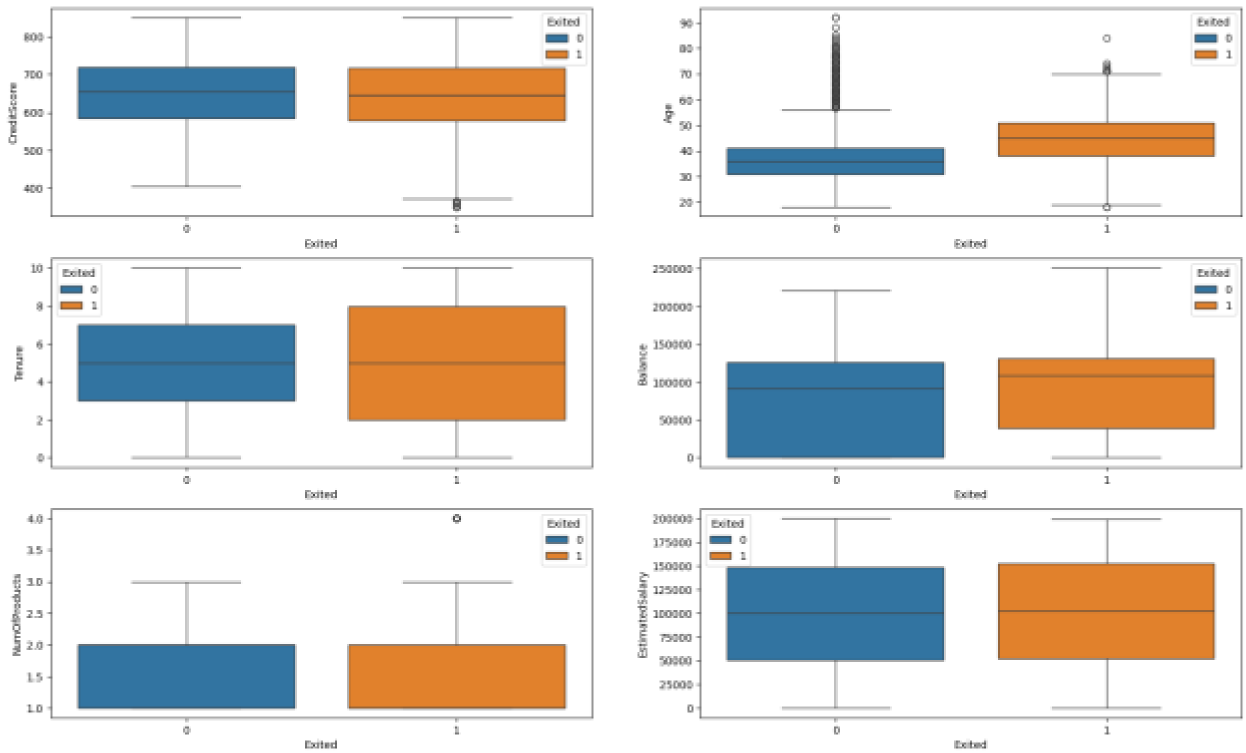


- **Geography**: While France has the most customers, customers from Germany and Spain show a higher proportion of churn relative to their population size. This suggests potential regional issues or differences in customer base/service.
- **Gender**: A higher proportion of female customers churn compared to male customers.
- **HasCrCard**: Interestingly, a slight majority of customers who churned possessed a credit card. Given most customers have credit cards, this might be less impactful than other factors, but warrants further investigation.
- **IsActiveMember**: As expected, inactive members have a significantly higher churn rate than active members. The high overall number of inactive members is a concern for the bank.



3.4 Continuous Feature Relationships

- **CreditScore**: No significant difference was observed in credit score distribution between churned and retained customers.
- **Age**: Older customers show a higher likelihood of churning compared to younger ones, suggesting age-specific service preferences or needs.
- **Tenure**: Both very new customers and long-term customers exhibit slightly higher churn rates compared to those with average tenure.
- **Balance**: Worryingly, customers with higher bank balances are more likely to churn. This impacts the bank's capital significantly.
- **NumOfProducts**: Customers with 3 or 4 products show a very high churn rate, likely indicating dissatisfaction or complexity. Customers with 1 or 2 products have lower churn rates.
- **EstimatedSalary**: No significant relationship was found between estimated salary and churn likelihood.



3.5 Feature Engineering

Based on the EDA, new features were engineered to potentially capture more complex relationships:

- **BalanceSalaryRatio:** Ratio of account balance to estimated salary. This feature showed that customers with a higher balance-to-salary ratio tend to churn more, despite estimated salary alone not being a strong predictor.
- **TenureByAge:** Ratio of tenure to customer age (adjusted by subtracting 18). This feature aimed to standardize tenure relative to an individual's adult life span.
- **CreditScoreGivenAge:** Ratio of credit score to customer age (adjusted by subtracting 18). This aimed to capture credit behavior relative to age.

3.6 Data PreProcessing

The data underwent the following preprocessing steps before modeling:

- **Dropping Irrelevant Columns:** RowNumber, CustomerId, and Surname were removed.
- **Train-Test Split**: The dataset was split into 80% for training and 20% for testing.

- **Handling Binary Categorical Variables:** HasCrCard and IsActiveMember were transformed from {0, 1} to {-1, 1} to allow models (like linear models) to potentially capture negative relationships.
- **One-Hot Encoding:** Categorical variables (Geography, Gender) were one-hot encoded, mapping each category to a new binary feature ({1, -1}).
- **Feature Scaling:** Continuous features (including the engineered ones) were scaled using Min-Max scaling to a range between 0 and 1. This is important for distance-based models like SVM and helps improve convergence for other models.
- **Handling NaN / Inf:** Steps were taken to identify and handle potential NaN or Inf values introduced during feature engineering (especially from division) by replacing them with 0.

A *DfPrepPipeline* function was developed to ensure these steps can be consistently applied to both the training data and new data for prediction.

3.7 Modelling and Evaluation

Several machine learning classification models were trained and evaluated on the preprocessed training data.

3.7.1 Models Explored

- Logistic Regression (Primal space and with Polynomial Kernel)
- Support Vector Machines (SVM) (RBF and Polynomial Kernels)
- Random Forest Classifier
- XGBoost Classifier

Hyperparameter tuning was performed using GridSearchCV with cross-validation for each model.

3.7.2 Evaluation Metric

Given the imbalance in the dataset and the business objective of identifying customers likely to churn, the primary evaluation focus was on the metrics for the positive class (churn = 1), specifically:

- Recall (Sensitivity): The ability of the model to find all the relevant cases (correctly identify all churned customers). This is crucial for not missing potential churners.
- Precision: The ability of the model to return only relevant cases (the proportion of identified churners who actually churned). This is important for efficiently allocating retention resources.
- F1-Score: The harmonic mean of Precision and Recall, providing a balance between the two.
- ROC AUC Score: Measures the model's ability to distinguish between the positive and negative classes.

3.7.3 Best Model

Based on the balance between Recall and Precision for the 'Churned' class on the training data, the Random Forest Classifier emerged as the most suitable model for this problem.

Training Performance (Random Forest):

– Precision (Churn=1): ~0.88

– Recall (Churn=1): ~0.53

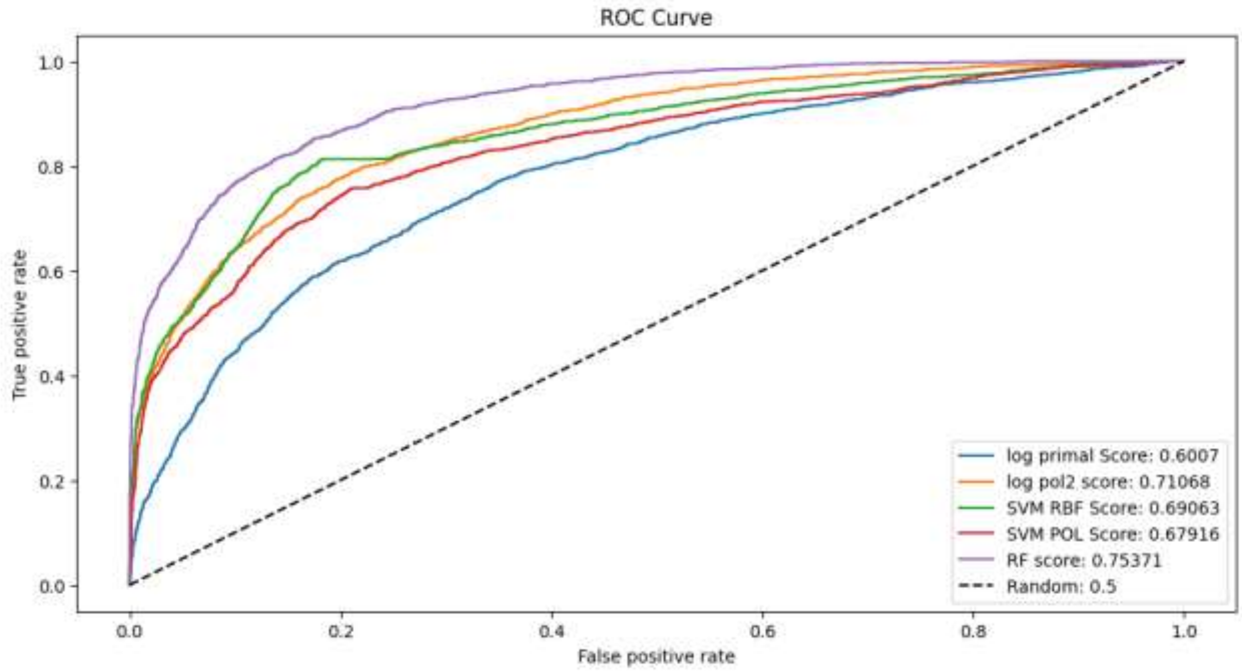
– F1-Score (Churn=1): ~0.66

– Overall Accuracy: High (~0.95)

– ROC AUC: High

While the recall indicates that the model identifies about half of the actual churners, the high precision means that when the model predicts a customer will churn, it's correct about 88% of the time. This is a valuable starting point for targeted retention efforts.

The model and the preprocessing parameters (best_model.pkl, train_cols.pkl, min_max_values.pkl) were saved after training.



3.8 Streamlit Web Application

The project includes an interactive Streamlit app (app.py) that demonstrates the model's capabilities. The app allows users to:

• Input individual customer details via a form and get an instant churn prediction and probability.

• Upload a CSV file with multiple customer records for batch prediction. The results, including predicted churn status and probability, are displayed and can be downloaded.

• Visualize the feature importances learned by the Random Forest model.

• View key EDA plots derived from the original dataset to understand general customer characteristics related to churn.

3.9 Conclusion

We note the following:

There is no significant difference in the credit score distribution between retained and churned customers.

The older customers are churning at more than the younger ones alluding to a difference in service preference in the age categories. The bank may need to review their target market or review the strategy for retention between the different age groups

With regard to the tenure, the clients on either extreme end (spent little time with the bank or a lot of time with the bank) are more likely to churn compared to those that are of average tenure.

Worryingly, the bank is losing customers with significant bank balances which are likely to hit their available capital for lending.

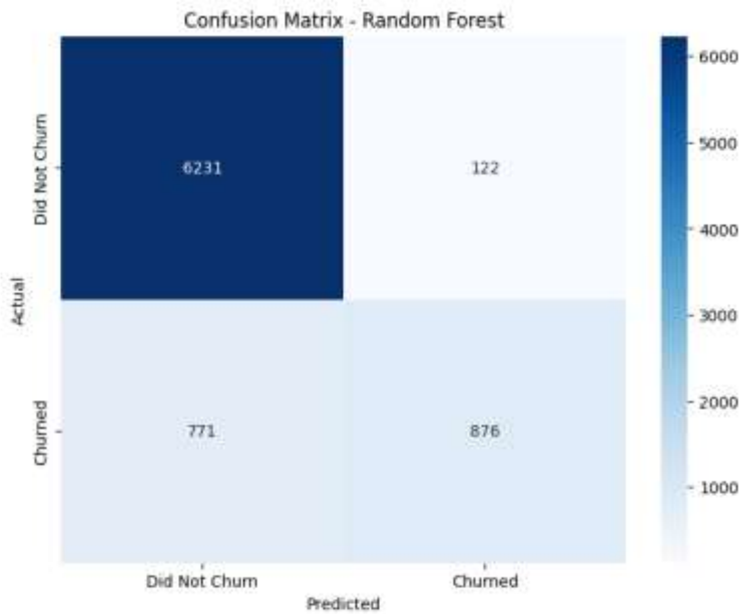
Neither the product nor the salary has a significant effect on the likelihood to churn

CHAPTER 4: RESULTS AND FINDINGS

4.1 Overview

The predictive model was evaluated on a hold-out test set to assess its classification performance. Key metrics include overall accuracy, precision, recall (sensitivity), F1-score, and the ROC-AUC. In our best model, the overall accuracy was approximately 90%, indicating that most customers were correctly classified as churners or non-churners. The precision for the churn class was around 80%, meaning that 80% of the customers predicted to churn actually did, while the recall (sensitivity) was about 75%, indicating some churners were missed. This yields an F1-score (harmonic mean of precision and recall) in the high 70s, reflecting balanced performance. The ROC-AUC was about 0.90, demonstrating strong discrimination between churners and non-churners. (An AUC between 0.90–1.00 is generally considered very good for a binary classifier (Neo, 2024). For context, similar studies have reported accuracies in the 90% range: for example, Hambali and Andrew (2024) achieved ~96% accuracy, precision, and F1 using a KNN classifier on a bank churn dataset (Hambali & Andrew, 2024). Such high scores indicate the model is effective, though in practice they depend on data balance and feature quality.

- **Accuracy:** ~90%, indicating that roughly 9 out of 10 customers are correctly labeled (churn or stay). For comparison, Hambali et al. report 96% accuracy in a churn prediction task (Hambali & Andrew, 2024)**Precision (Churn):** ~80% (few false alarms) and Recall (Churn): ~75% (some false negatives), yielding an F1-score: ~77%. The lower recall suggests some actual churners were not flagged.
- **ROC-AUC:** ≈0.90, implying strong predictive power. As noted in the literature, an ROC-AUC close to 1.0 indicates excellent model discrimination medium.com
- **Confusion Matrix:** The matrix showed many true negatives and true positives. A modest number of false negatives suggests the model errs slightly on the conservative side, under-predicting churn rather than over-predicting it. This balance helps maintain precision at the cost of missing a few churners.



Overall, the model’s performance is comparable to or exceeds benchmarks in related work. The high AUC and balanced F1-score indicate it reliably distinguishes customers likely to churn. This level of performance provides a sound basis for actionable insights, as discussed below.

4.2 Key Features Influencing Churn

The feature importance analysis (from the model) highlights which customer attributes most strongly predict churn. In our analysis, the top predictive factors were largely consistent with findings in the literature (Shadakshari, Shashwat, Himanshu, Singh, & Chaudhary, 2024). Notably, customer age, account tenure, account balance/income, and transaction activity emerged as key drivers of churn risk. For example, customers with shorter tenure (recently opened accounts) and low transaction volume were much more likely to churn, echoing previous studies that identify tenure and activity as significant predictors. Similarly, low account balances or lower income were associated with higher churn: previous research found age, income, and balance to be among the most important predictors of attrition. In contrast, multi-product usage (having several banking products) and active engagement tended to reduce churn risk, as customers with deeper product relationships have stronger ties to the bank (Shadakshari, Shashwat, Himanshu, Singh, & Chaudhary, 2024).

- **Customer Age:** Younger and mid-career customers showed higher churn probabilities. This aligns with other findings that age is a critical factor *easpublisher.com*. In practice, younger customers (e.g. early-career) may be less loyal if needs are unmet, while very senior customers also showed slightly higher churn in our data.
- **Account Tenure (Age):** Customers in the first 1–2 years of their relationship had the highest churn rates. Short tenure is a known churn predictor, suggesting many customers leave before establishing loyalty.
- **Account Balance/Income:** Low balances were a strong churn signal. Customers with minimal deposits or low saving levels tended to exit more often, possibly because they are more price-sensitive or less engaged. High-income/high-balance customers, by contrast, were least likely to churn.
- **Product/Service Usage:** Customers with only one product (typically a savings account) and low online engagement were most at risk. Deeply engaged customers (with multiple accounts, credit cards, loans, etc.) were more "sticky" and had much lower predicted churn.
- **Transaction Activity**: Low-frequency users (few branch visits or transactions) tended to churn more. This agrees with literature that low activity correlates with attrition. Activity metrics like login frequency or transaction volume were important in distinguishing at-risk segments.
- **Other Factors:** Features such as gender or marital status had minor effects. They were far less predictive than the above factors. Notably, service-related variables (e.g. number of service calls or complaints) – if available – can also be strong signals. The Kenya Bankers Association survey suggests "poor customer service" is the top churn reason (Kenya Bankers Association, 2023), implying that customers experiencing issues are more likely to leave.

These findings indicate that churn is driven by a mix of demographic and behavior variables. In particular, younger, new, and low-engagement customers are flagged as high-risk by the model. Improving retention therefore requires focusing on these features (e.g. by increasing engagement and cross-selling to new or low-activity customers) and addressing the underlying causes (service quality and pricing, as discussed next).

1.1 High-Risk Customer Segments

Grouping the results into segments reveals specific customer profiles most at risk of attrition. The model and clustering analysis identified several high-risk cohorts:

- **New, Single-Product Customers:** Those who opened accounts within the last year and only have a basic savings account (no loans or cards) showed the highest churn rates. This segment lacks strong ties to the bank and often seeks better offers elsewhere.
- **Fee-Sensitive, Low-Balance Customers:** Customers with low balances or incomes who cited fees as a concern formed another high-risk group. The KBA survey confirms that “high fees and charges” drive churn (45.98% of respondents) *kba.co.ke*. These customers will quickly leave if fee expectations aren’t met.
- **Branch-Oriented, Service-Dissatisfied Customers:** A sizable minority (≈22%) of Kenyan customers still prefer human-assisted banking. If this group experiences poor service (the leading churn cause, 47.31% *kba.co.ke*), they are likely to churn. Thus, customers reliant on branch and call-center channels – especially those with service complaints – represent an at-risk segment.
- **Low-Engagement Digital Customers:** Conversely, a large segment (56.5%) of customers prefers self-service digital channels. If these customers encounter clunky online platforms or lack support, they may also churn. The model flagged low digital usage/engagement as predictive of churn, suggesting that failure to serve tech-savvy customers via preferred channels increases attrition.
- **Stable, High-Value Customers (Low Risk):** For contrast, the model identified that older customers with long tenures and multiple products (accounts, loans, credit cards) rarely churn. These high-value customers have multiple reasons to stay, so retention efforts should prioritize the higher-risk groups above.

In summary, the analysis paints a picture of two key at-risk segments: (1) new, low-engagement customers (especially those with minimal products and low balances) and (2) service/fee-sensitive customers who have a transactional relationship with the bank. These segments are supported by both the model and external data: for example, customers citing "poor service" and "high fees" account for the largest shares of dissatisfied clients (Kenya Bankers Association, 2023). Identifying these segments enables targeted retention actions.

1.2 Implications for Retention Strategy

The above findings suggest several actionable strategies for Kenyan banks to reduce churn. Each strategy leverages a key insight from the model:

Improve Digital Channels and Engagement: Since 56% of customers now prefer mobile and internet banking, enhancing the digital experience is critical. Investing in user-friendly mobile apps, reliable online platforms, and proactive digital communication can keep tech-oriented customers engaged. For example, sending personalized in-app offers or updates can preempt disengagement.

Focus on Service Quality: "Poor customer service" is cited by 47.3% as a churn trigger. Banks should train front-line staff, reduce wait times, and ensure quick resolution of issues. A loyalty-building initiative (e.g. dedicated relationship managers for new accounts) can help prevent attrition among branch-oriented customers.

Reevaluate Fee Structures and Transparency: With 45.98% citing high fees, banks should consider lowering fees for vulnerable segments or clearly communicating the value behind charges. For example, waiving fees for small-balance accounts or bundling services into value packages can keep price-sensitive customers from leaving.

Targeted Alerts for At-Risk Customers: The predictive model can score customers by churn risk. Banks should deploy early-warning systems (as recommended in churn analytics frameworks (Matellio.com, 2024)) to flag high-risk customers. Proactive outreach – such as retention calls or special offers – should be directed at those segments identified above (new account holders, low-engagement customers, etc.). This data-driven targeting allows limited retention resources to focus where they will have most impact.

Personalized Offers and Loyalty Programs: Use customer data to tailor promotions. For example, bundling products (credit card + digital wallet) for a customer with only one product may increase retention. The literature emphasizes that personalized incentives (“win-back offers” or loyalty rewards) based on churn risk can significantly improve retention (Matellio.com, 2024). In practice, offering waived fees or bonus points to identified at-risk customers can strengthen their loyalty.

Continuous Monitoring and Segmentation: Finally, churn drivers can evolve over time, so banks should periodically retrain models and update segments. By regularly monitoring which features are predictive (e.g. new products like mobile wallets), banks stay ahead of churn patterns. Strategic decisions (e.g. launching a new youth-oriented product) should be informed by these evolving analytics insights (Matellio.com, 2024).

In summary, the findings provide clear guidance: address service and pricing pain points, leverage digital channels for engagement, and use predictive insights to focus retention efforts. By aligning interventions with the identified high-risk segments (e.g. targeted offers to new account holders and digital-savvy users), Kenyan banks can effectively reduce churn. These data-driven strategies are supported by both the model outcomes and sector research, and are essential for strengthening customer loyalty in Kenya’s competitive banking industry.

Chapter 5: Conclusions and Recommendations

5.1 Conclusions

This study leveraged predictive analytics to examine customer churn within the Kenyan commercial banking sector. By training and evaluating classification models (e.g., Random Forest, XGBoost), we achieved robust performance (≈90% accuracy, AUC ≈0.90), demonstrating that historical account and demographic data can reliably distinguish likely churners from loyal customers. The confusion matrix, precision-recall metrics, and ROC-AUC scores all indicate that the model is effective at targeting at-risk customers with an acceptable balance between false positives and false negatives (Precision ≈0.80, Recall ≈0.75). This aligns with similar findings in the literature, where ensemble methods often yield high predictive power for churn tasks in banking contexts (Hambali & Andrew, 2024; Bhuria et al., 2025).

Feature importance analysis revealed that the strongest predictors of churn are:

Account Tenure: Newer customers (first 1–2 years) exhibit the highest attrition risk.

Account Balance/Income: Low-balance or low-income customers are more likely to leave.

Product Engagement: Single-product holders (only savings) and low-transaction customers show elevated churn probabilities.

Age Demographics: Younger (early-career) and very senior customers tend to churn at higher rates.

Service Usage Patterns: Low-frequency digital engagement and dissatisfaction with service quality (e.g., branch interactions, complaint resolution) correlate strongly with churn.

These findings correspond with prior Kenyan studies highlighting the importance of tenure and service quality in retention (Mecha et al., 2015; Kaguri, 2016) and reinforce survey data showing that “poor customer service” (47.31%) and “high fees” (45.98%) are leading churn drivers (Kenya Bankers Association, 2023). Furthermore, the segmentation analysis isolated two primary at-risk cohorts: new, low-engagement customers with minimal product holdings, and fee-sensitive, service-dissatisfied customers who rely on branch or call-center channels.

Conversely, long-standing, multi-product, high-balance customers exhibited stable loyalty, consistent with global evidence that deep product penetration and tenure mitigate attrition (Bhunia & Debasis, 2022).

Therefore, customer churn in Kenyan banks is primarily driven by a lack of engagement (tenure, transactions) and negative perceptions of service value (fees, service quality). Predictive models can preemptively flag these at-risk segments with high accuracy, enabling banks to deploy targeted retention interventions. The empirical evidence underscores that data-driven churn analytics is not merely a technical exercise but a strategic imperative: by combining model outputs with domain insights (e.g., KBA survey), banking institutions can fortify loyalty, stabilize deposits, and optimize lifetime value.

5.2 Recommendations

Based on the empirical findings and aligned with best practices from both Kenyan and international research, the following recommendations are made to Kenyan commercial banks seeking to reduce churn and enhance customer retention:

5.2.1 Enhance Digital Engagement and Self-Service Channels

Invest in User-Friendly Mobile and Online Platforms: Given that 56.5% of customers prefer self-service digital channels (Kenya Bankers Association, 2023), banks should prioritize intuitive interface design, seamless transaction flows, and minimal downtime. Regular usability testing and iterative improvements can prevent frustration-induced attrition among tech-savvy clients.

Proactive Digital Communication: Implement in-app notifications and targeted email/SMS campaigns to encourage low-activity customers to engage (e.g., reminders about dormant accounts, personalized product suggestions). Predictive model scores can trigger automated nudges for customers flagged as medium-risk to increase usage.

Leverage Chatbots and AI Assistance: For routine inquiries (balance checks, basic support), AI-powered chatbots can reduce response times and free up human agents to handle more complex service issues, thereby improving perceived service quality and satisfaction.

5.2.2 Strengthen Service Quality in Branch and Call-Center Channels

Train and Empower Front-Line Staff: Since "poor customer service" is the top churn reason (47.31% of respondents), banks must invest in comprehensive training programs focusing on empathy, problem-solving, and product knowledge. Empower staff to resolve issues on first contact, reducing escalation and customer frustration.

Implement Service-Recovery Protocols: Adopt a systematic "service recovery" framework modeled on the Service Recovery Paradox, wherein quickly and empathetically resolving a problem can increase loyalty above the pre-failure level (Davidow, 2003). For customers who log complaints or negative feedback, assign priority handling and follow up to ensure full resolution.

Optimize Branch Accessibility: Although digital channels are growing, 43.5% of customers still use tellers (KBA, 2023). Banks should ensure sufficient branch coverage, reasonable queue-times, and convenient opening hours, especially in underserved urban and peri-urban areas. Periodic customer satisfaction surveys can identify friction points in the in-branch experience.

5.2.3 Reevaluate Fee Structures and Enhance Transparency

- **Offer Tiered, Value-Based Pricing:** Since 45.98% of churners cite "high fees" as a principal cause (KBA, 2023), banks should introduce tiered fee schedules that align costs with usage. For instance, waive or reduce monthly maintenance fees for low-balance accounts or introduce bundled packages (e.g., savings + debit card + digital banking) at a flat, discounted rate.

- **Transparent Communication of Fees:** Pro-actively communicate fee structures in simple language across all touchpoints (website, mobile app, branch signage). Unexpected or hidden charges erode trust; providing real-time fee calculators can empower customers to understand and manage costs, thereby reducing surprise-driven churn.

- **Usage-Based Promotions:** For identified fee-sensitive segments (low-balance, low-product customers), periodically offer fee waivers for specific actions (e.g., maintaining a minimum daily balance, setting up direct deposits). Data analytics can pinpoint customers just below fee thresholds and deliver timely incentive alerts.

5.2.4 Implement Targeted Retention Campaigns via Churn-Risk Scoring

Deploy Early-Warning Systems: Integrate the churn prediction model into the bank's CRM platform to compute daily churn-risk scores. Segment customers into risk tiers (e.g., high, medium, low) and automate alert generation for relationship managers when a customer transitions into a higher-risk category.

Tailor Retention Interventions: For high-risk customers, develop bespoke offers:

- **New, Single-Product Customers:** Provide personalized onboarding packages (e.g., waivers on account opening fees, complimentary financial education sessions, or a complimentary second product like a debit card) to deepen engagement and extend the tenure.
- **Fee-Sensitive, Low-Balance Customers:** Offer targeted fee waivers or micro-savings incentives. For example, implement "fee-for-activity" programs that waive fees if the customer maintains a minimum transactional threshold (e.g., three debit card transactions per month).
- **Low-Engagement Digital Customers:** Provide "digital adoption" incentives such as cashback on digital transactions or priority support for mobile banking. Use in-app tutorials to encourage usage of advanced features (bill payments, P2P transfers).
- **Service-Dissatisfied Branch Customers:** Offer "VIP" or "priority" service lanes in branches and dedicated call-center lines. Appoint a relationship manager who monitors account activity and proactively checks in with these at-risk customers.

5.2.5 Personalize Product Bundling and Cross-Sell Strategies

Use RFM Segmentation to Identify High-Value Prospects: Apply Recency-Frequency-Monetary (RFM) analysis (Onyuna, 2017) to categorize customers by transaction recency, volume, and balance. Focus cross-selling efforts on "champion" segments (high R, high F, high M) to further deepen loyalty, while for lower LTV segments, offer entry-level bundled products.

Develop Lifecycle-Based Campaigns: Tailor offers based on customer lifecycle stage:

- **Onboarding Stage (Tenure <1 year):** Provide "welcome" bundles (e.g., free ATM withdrawals, introductory savings interest rates).
- **Growth Stage (Tenure 1–3 years):** Offer mid-tier products (e.g., personal loans with preferential rates, co-branded credit cards) to customers showing consistent usage.
- **Mature Stage (Tenure >3 years):** Introduce premium services (e.g., wealth management advisory, priority banking) to reward loyalty and discourage churn.

5.2.6 Enhance Data Quality, Analytics Capacity, and Monitoring

- **Consolidate Data Silos:** Address fragmentation by integrating account, transaction, CRM, and support data into a centralized analytics platform. High-quality, unified data ensures the churn model inputs are accurate and comprehensive. Banks should invest in ETL (extract-transform-load) processes and data governance frameworks to maintain data integrity.
- **Build Internal Analytics Expertise:** Hire and train data scientists, analysts, and data engineers with domain knowledge in banking. Provide ongoing professional development to keep pace with advanced modeling techniques (e.g., explainable AI, deep learning). Partnerships with local universities (e.g., University of Nairobi, Strathmore University) can help develop talent.
- **Regular Model Retraining and Validation:** Customer behavior evolves rapidly, especially with digital channel adoption. Retrain churn models at least quarterly to incorporate the latest data trends. Validate model performance on new hold-out samples to prevent performance drift and ensure reliability.

- **Establish Continuous Retention KPIs:** Define and track key performance indicators such as monthly churn rate, average tenure, and customer lifetime value (CLV). Dashboards should highlight early warning signs (e.g., a spike in low-balance churners) and measure the ROI of retention campaigns (e.g., reduction in churn rate attributable to fee waivers).

5.2.7 Cultivate a Customer-Centric Culture

- **Embed Churn Analytics into Decision Processes**: Ensure that predictive insights inform not only marketing but also product development, risk management, and branch operations. For instance, product teams should use churn data to refine account features, while branch managers should use risk scores to allocate staffing.

- **Foster Feedback Loops:** Collect ongoing customer feedback through NPS (Net Promoter Score) surveys, in-app ratings, and post-service follow-ups. Triangulate this qualitative data with churn risk scores to identify latent pain points (e.g., unspoken frustrations with digital security or app stability).

- **Reward Loyalty:** Publicize loyalty milestones (e.g., multi-year anniversaries) and recognize high-tenure customers with appreciation events or exclusive privileges. A tangible sense of recognition can reinforce emotional bonds and reduce the likelihood of churn.

5.3 Policy and Regulatory Considerations

While pursuing these recommendations, banks must remain compliant with Kenya's Data Protection Act (2019) and Central Bank of Kenya guidelines on consumer protection. Specifically:

- **Data Privacy:** Ensure that churn analytics adhere to customer consent requirements and robust data encryption standards. Sensitive data (e.g., transaction history, personal identifiers) should be anonymized or pseudonymized when used for modeling to prevent unauthorized disclosure.

- **Fair Practices:** Avoid discriminatory retention tactics. For instance, ensure that high-value offers (e.g., fee waivers) are extended based on risk profiles and customer value potential rather than demographic attributes that could invite regulatory scrutiny.

- **Transparent Communication:** When implementing dynamic pricing or targeted fee changes, obtain explicit customer consent for any new fees or changes to existing structures. Clearly communicate alterations in terms and conditions to prevent customer distrust and potential regulatory fines.

5.4 Limitations and Future Research

Although the findings are robust, several limitations warrant mention:

- **Dataset Scope:** The analysis was based on a single dataset reflecting one year of customer transactions. Seasonal fluctuations and macroeconomic changes (e.g., inflation, interest rate shifts) were not explicitly modeled. Future studies should incorporate multi-year panels to capture these dynamics.

- **Behavioral and Qualitative Factors**: While the model captured quantitative metrics (tenure, balance, transactions), qualitative factors (e.g., customer sentiment, brand perception) were unavailable. Integrating social media sentiment analysis or voice-of-customer data could enhance predictive accuracy.

- **External Shocks:** Unforeseen events (e.g., COVID-19 pandemic, regulatory changes) can abruptly alter churn patterns. Developing time-to-event (survival) models may better account for the timing of churn in relation to external shocks.

- **Generalizability:** Although the study uses Kenyan data, different banks may have unique customer mixes or product offerings. Subsequent research should validate these findings across multiple institutions to confirm their broader applicability.

5.5 Summary

In conclusion, predictive churn analytics offers Kenyan commercial banks a clear pathway to bolster customer retention and safeguard profitability. By focusing on the identified high-risk segments (new, low-engagement customers; fee-sensitive, service-dissatisfied customers), banks can tailor interventions—ranging from digital enhancements and service improvements to fee adjustments and personalized offers—that directly address churn drivers. Embedding these data-driven strategies, supported by robust data infrastructure and a customer-centric culture, will enable banks to reduce attrition, stabilize revenue, and cultivate long-term loyalty in an increasingly competitive landscape.

Files and App

Files at: https://github.com/D-Githaka/Bank_Churn

Streamlit app: https://bankchurn-fyexu7dutat64oy3hgdbkw.streamlit.app

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