Customer Segmentation & Churn Analysis Report

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Objective: Analyze customer behavior to identify key segments, predict churn, and recommend actions to increase retention and customer lifetime value.

1. Demographic Clustering Analysis

Using clustering techniques, customers were grouped into **8 distinct clusters** based on age, gender, and marital status.

Key findings:

Cluster	Count	Avg Age	Top Age Group	Top Gender	Top Marital Status
0	129	44.0	<30	F	Married
1	107	43.6	<30	M	Single
2	150	43.5	<30	F	Widowed
3	126	43.9	<30	F	Divorced
4	132	43.0	<30	M	Married
5	126	43.0	<30	M	Widowed
6	122	42.7	<30	M	Divorced
7	108	42.3	<30	F	Single

Insights

- **<30 age group dominates**, though average age hovers in the 40s — suggesting a broad customer mix but skewed toward younger users.
- Gender and marital status vary by cluster: married and widowed customers appear most often.
- **Younger, single individuals show lower churn**, while **married and widowed customers churn more**.

2. RFM & Risk Segmentation

RFM modeling and risk flags categorize customers by value and engagement:

Segment Distribution:

- **Loyal**: 307
- **At Risk**: 172
- **Champions**: 66
- Others: 455 (Recent, Frequent, Others)

Risk Flags:

- **At Risk**: 519
- **Monitor**: 260
- **Safe**: 221

Insights

- **Champions and Loyal segments** represent your high-value base. They should be nurtured through loyalty programs and exclusive benefits.
- **At-Risk and Monitor segments** require targeted interventions, especially among disengaged older demographics.
- **Churned customers tend to log in less, transact less**, and are more likely to be **older, married, or widowed**.

Strategic Takeaways

- Focus marketing on young, single, digital-native customers for acquisition.
- Build retention journeys for older, married, and widowed customers — offer hybrid/digital support.
- Design product bundles or services tailored by cluster profiles.

Predictive Churn Modeling & Next Actions

Churn Prediction Model Summary

A machine learning model was built using a **Random Forest Classifier** trained on customer activity, transactions, and profile data.

Model Highlights:

Class	Precision	Recall	F1-Score	Support
Non-Churn (0)	0.90	0.97	0.93	212
Churn (1)	0.90	**0.73**	0.81	88
Overall Accuracy	—	—	**90%**	300

What This Means:

- The model can **identify 73% of churners** ahead of time — enabling **proactive intervention**.
- With **90% precision**, the model offers **actionable, high-confidence predictions** for churn.
- The model also maintains high accuracy for non-churners — ensuring efforts are well-targeted.

Retention & Growth Strategy

1. Proactive Churn Prevention

Use model output to:

- Identify churn-likely customers **before they leave**
- Launch **targeted re-engagement campaigns** (e.g., bonus offers, check-ins)
- Prioritize support for **high-risk segments** like married and widowed customers

2. Monetize Predictions Through Cross-Selling

- Use predicted churners as a high-impact group for **retention + upsell offers**.
- Bundle services that **increase stickiness** (e.g., savings accounts, loyalty perks, digital tools).

3. Tailored Experiences

Combine model output with cluster insights to offer:

- Young customers: digital-first services

- Older customers: hybrid or human-centric support
- Widowed/divorced: financial planning and personalized care

Next Steps

Initiative	Action Owner	Priority
Launch retention campaigns	Marketing Team	High
Design loyalty offers for clusters	Product Team	Medium
Set up churn alert automation	Data Engineering	High
Monitor model performance monthly	Analytics	Medium

Final Thoughts

The churn model provides a **data-driven edge** in retaining valuable customers. With **73% of likely churners identified**, the bank now has the power to **intervene at the right time** and **boost retention with confidence**. Combined with customer segmentation insights, this enables **hyper-personalized service and smarter growth**.