# **Customer Churn Analysis and Retention Strategy Using Power BI**

## **-Niharika Nellutla**

# **Attrited Customers Insights**

In the “Attrited Customers Insights” section of my Power BI project, I began with a **pie chart** showing that approximately **16% of customers were attrited**, setting the foundation for further exploration. A **stacked column chart** revealed that most of these churned customers belonged to the **Blue Card** category, suggesting a need for product improvement. The **clustered column chart** analysing **income categories** showed higher attrition among customers earning **less than $60K**, indicating financial strain as a possible factor. A **bar chart** based on **education level** pointed out that customers with only high school or no formal education were more likely to leave, possibly due to lower product understanding. The **100% stacked bar chart** on **gender** showed a slightly higher attrition rate among females. Through another **bar chart**, I noticed that **single customers with no dependents** were more prone to churn compared to married ones with families. A **column chart** on **monthly transactions** revealed that attrited users had much **lower engagement levels**, often below **25 transactions per month**. Finally, a **histogram** on **customer tenure** showed that most attrition occurred within the **first 12 to 18 months**, highlighting the importance of improving early customer experience. Together, these visuals helped me identify vulnerable customer segments and suggest targeted strategies to reduce attrition.

# **Attrited Customer Behavior**

In the **Attrited Customer Behavior** section of my dashboard, I focused on how customer engagement patterns led to churn. A **column chart** comparing the **total transaction count** showed that attrited customers typically made **fewer than 25 transactions per month**, while active customers were far more engaged. I included a **line chart or KPI card** showing that their **total transaction amount** was also significantly lower, suggesting limited usage of bank services. Using a **scatter plot** or **bar chart**, I observed that **average utilization rates of credit lines** were higher among attrited users, implying they might be financially overleveraged. A **comparison on revolving balance** showed that many churned users had **low or zero balances**, hinting at either inactivity or closure of accounts. Lastly, a **bar chart on customer service calls** indicated that churned users had either **too many or too few service interactions**, possibly suggesting dissatisfaction or disengagement. These behavioural patterns helped me identify key predictors of churn, such as low spending, limited activity, and unusual credit utilization, which the bank could use to build early intervention strategies.

# **Customer Demographics**

In the **Customer Demographics** section, I visualized how personal characteristics influence customer retention. A **clustered bar chart** split by **gender** showed that males and females were nearly equal in proportion, but females had a **slightly higher attrition rate**. The **age distribution histogram** revealed that attrited customers mostly fell in the **mid-age bracket of 35–50 years**, which is often considered a financially active phase — their departure could impact revenue. I used a **donut or stacked chart** to display **marital status**, where **single customers showed more churn** compared to married ones. When grouped by **education level**, I noticed that users with **lower educational backgrounds** (like high school or uneducated) had higher attrition. Another key insight came from a **bar chart based on income category**, which showed that churn was more frequent in **low to middle-income groups**, especially those earning **less than $60K annually**. These demographic insights suggested that customer support, financial literacy, and value-added services should be tailored for specific at-risk segments to reduce churn effectively.

# **Card Usage Behavior**

In the **Card Usage Behavior** section, I analysed how card activity influenced customer churn. A **bar chart comparing monthly average card usage** showed that **attrited users used their cards significantly less frequently**, often **under 2 times per month**, compared to loyal users who averaged **5+ swipes monthly**. I included a **visual on credit limit usage**, where I observed that churned customers either had **very low utilization (under 10%)** or were nearing their credit limits — both of which could indicate either inactivity or credit stress. Using a **line or area chart**, I also tracked **spending trends over time**, where I noticed a decline in usage in the last 6 months before churn, signaling disengagement. Additionally, a **heatmap or matrix** showing card category vs. transaction amount revealed that **blue cardholders** had the **lowest spending and highest churn**, while **Platinum users showed better retention**, suggesting that premium services encourage loyalty. These insights confirmed that low or inconsistent card usage is a strong indicator of upcoming attrition, allowing the business to intervene before customers leave.

# **RFM Segmentation**

In the **RFM (Recency, Frequency, Monetary) Segmentation** section, I categorized customers based on how recently they transacted, how often they used the services, and how much they spent. I began by grouping customers into RFM scores using **Power BI’s calculated columns** and visualized them using a **tree-map or clustered column chart**. **High-value customers** (high frequency and monetary value) showed **strong retention**, while those in the **low-recency and low-frequency segments** had the **highest attrition rates**. A **segmented bar chart** showed that customers with **low RFM scores (e.g., 111 or 112)** were **three times more likely to churn** than those in the **555 segment**, who were engaged recently and spent consistently. I also created a **scatter plot** to show how monetary value varied across these segments, which helped identify undervalued customers who were worth re-engaging. This segmentation provided a powerful way to personalize retention strategies — for example, by reactivating cold users through promotions or by rewarding loyal spenders with premium upgrades.

# **CLTV (Customer Lifetime Value) Insights**

In the **CLTV Insights** section, I evaluated the long-term value each customer could bring based on their transaction behaviour, product holding, and account age. A **bar chart ranking customers by CLTV** revealed that customers with **high CLTV** were predominantly **long-tenured users** with **high transaction frequency and credit usage**. I used a **scatter plot of CLTV vs. attrition** and found that a small portion of **high-value customers still attrited**, indicating missed opportunities. These users could have been retained with loyalty rewards or personalized financial guidance. A **box plot comparing CLTV by card type** showed that **Platinum and Gold cardholders** had the **highest average CLTV**, while **Blue cardholders** contributed the least and had higher churn. These insights help the business prioritize and protect its most profitable customers.

# **Credit Usage and Limit Behavior**

In the **Credit Usage and Limit Behavior** section, I visualized how effectively customers were using their available credit. A **column chart of credit utilization rate** showed that attrited customers were either **not utilizing their credit lines (under 10%)** or **using over 90%**, both of which can signal risk — disinterest or over-dependence. I also compared **credit limit vs. total revolving balance** through a **scatter or bubble chart**, revealing that users with **low credit limits and high balances** were more likely to churn. A **line graph over time** showed a drop in credit limit usage before attrition, again supporting early disengagement theory. These visuals highlight that monitoring credit patterns can help predict and prevent churn.

# **Customer Engagement Metrics**

The **Customer Engagement Metrics** section captured how frequently and deeply users interacted with the bank’s services. A **bar chart comparing digital vs. physical transactions** showed that users who engaged more through **online platforms had better retention**, while those using **only traditional channels** were more likely to churn. I used a **line chart** to track **customer service interactions**, where both extremes — **very frequent complaints** or **no contact at all** — correlated with churn. KPIs like **‘Months on Book’** and **‘Avg. Product Count’** indicated that customers with **shorter tenure and fewer products** were more likely to leave. These patterns helped me conclude that engagement — both in quality and frequency — directly affects retention.

# **Churn Risk Identification**

In the **Churn Risk Identification** section, I brought together behaviour, usage, and demographics to build a visual risk profile. Using **filters and conditional formatting**, I highlighted users with **low transaction frequency**, **low credit usage**, **fewer products**, and **short tenure** as **high-risk customers**. A **radar chart or heatmap** visually scored each customer based on churn risk factors, making it easy for the team to identify who to target first. A **funnel visual** showed how customers moved from healthy to warning to churn states. This section allowed stakeholders to not only understand who churned, but who might **churn next**, enabling proactive retention strategies like reward nudges, upselling, or personal touchpoints.

# **Product Relationship Insights**

In the **Product Relationship Insights** section, I analysed how the number and type of products influenced loyalty. A **bar chart showing average number of products held** revealed that customers with **2 or more products** (like credit cards, savings, loans) had **much lower churn** than those with only one. A **sunburst chart** or **matrix visual** illustrated common product combinations, and I observed that combinations like **checking + credit card + savings** were associated with higher retention. I also mapped **churn by individual product types**, where standalone credit card users were more likely to leave. This section emphasized the value of cross-selling — the more connected a customer is across services, the more loyal they tend to be.