ABC Bank Credit Card Customer Risk & Profitability Analysis

Turning Risk Detection into Sustainable Profitability

Profit Analysis & Business Impact

⚙️ Methodologies

- 📊 Focused profitability analysis on customers flagged 'in need of attention'.
- 💰 Calculated profit per customer, summarized at-risk vs. non-risk groups.
- 📉 Estimated potential profit loss exposure from at-risk customers.
- 🤖 Evaluated financial impact of predictive risk detection models.
- ✅ Linked profitability outcomes to engagement & loss prevention strategies.

💡 Key Insights

- 📉 Majority of at-risk customers are unprofitable, driving financial exposure.
- 💰 Potential **~$7.52M loss exposure** identified if no preventive measures are taken.
- 🚩 High-risk behaviors linked directly to reduced profitability (e.g., cash advances, low repayments).
- 🤖 Predictive risk detection enables early intervention to safeguard revenue.
- ✨ Business Impact: Strengthens profitability by converting risk detection into actionable prevention strategies.

✨ *Linking risk detection to profitability ensures sustainable financial growth and resilience.*

Our Approach

📌 Project Motivation

- 🛡️ Safeguard Portfolio Health – Detect early risk indicators.
- 🔄 Protect Business Resilience – Proactive, preventive measures.
- 🚀 Drive Growth in High-Value Segments – Convert low-tier to premium users.

⚙️ Approaches Overview

- 🧹 Data Preparation – Cleaned & preprocessed data for reliable insights.
- 👥 Segmentation & Profiling – Clustered customers, generated risk indicators.
- 🤖 Predictive Modeling – Automated risk detection model.
- 📈 Growth Analysis – Identified risky segments for conversion strategies.

✨ *Aligns with ABC Bank's vision of sustainable growth, financial resilience, and enduring customer trust.*

APPROACHES

Data Cleaning

⚙️ Methodologies

- 🧩 Missing Values Analysis – Identified missing data (CREDIT_LIMIT ≈0.011%, MINIMUM_PAYMENTS ≈3.5%).
- 📊 Imputation Strategy – Median imputation chosen due to strong right-skewness.
- ✅ Data Integrity Checks – Duplicate record verification.

📈 Results

- 🔷 CREDIT_LIMIT missing values imputed with median, preserving distribution integrity.
- 🔷 MINIMUM_PAYMENTS missing values imputed with median, reducing outlier effects.
- 🔷 No duplicate records found → High data quality ensured.

✨ *A robust data foundation established for segmentation and predictive modeling.*

Customer Segmentation

⚙️ Methodologies

- 🧹 Data Preparation – Cleaned, preprocessed, and applied feature scaling.
- 📊 Cluster Evaluation – Used Elbow Method, Silhouette Score, and DBI to identify optimal k.
- 👥 Segmentation Profiling – Interpreted customer groups for k=3 (broad) and k=7 (granular).
- ✅ Recommendation – Adopt k=7 for actionable strategies; k=3 for simplified executive view.

📈 Results

- 🔷 k=2 gave clear separation but oversimplified behavior.
- 🔷 k=3 provided broad clusters: revolvers, low-engagement, and spenders.
- 🔷 k=7 revealed nuanced subgroups: VIPs, loyal full-payers, dormant users, anomalies.
- 🔷 k=10 had strong metrics but impractical for business use.
- ✨ Final Recommendation: Use k=7 for targeted actions, k=3 for broad summaries.

✨ *Segmentation enables personalized marketing, improved risk management, and strategic growth.*

Risk Identification

⚙️ Methodologies

- 🧩 Defined key stress behaviors: high cash advances, low payments, high utilization, large minimum payments, irregular balances.
- 📊 Aggregated flagged behaviors into a unified Stress Score.
- 📌 Classified customers into Low, Medium, and High risk levels.
- 🚩 Introduced an Attention Flag to highlight customers needing proactive monitoring.
- ✅ Assigned business-friendly labels for better interpretability.

📈 Results

- 🔷 Built Stress Scoring Model consolidating multiple behaviors.
- 🔷 Generated interpretable Low, Medium, and High risk levels.
- 🔷 Attention Flag enabled proactive monitoring & predictive modeling.
- 🔷 Labels improved stakeholder understanding and EDA integration.

✨ *Stress Scoring provides a practical framework for customer risk management and proactive intervention.*

Risk Prediction

Methodologies

- Selected & preprocessed key numerical features.
- Removed correlated & high-VIF variables to address multicollinearity.
- Identified class imbalance (≈2.7:1) and prepared resampling strategies.
- Split dataset (80% train, 20% test) for unbiased evaluation.
- Applied feature scaling to normalize ranges & reduce outliers.
- Built baseline Logistic Regression; considered MLP, Random Forest, XGBoost.
- Evaluated with accuracy, F1, overfitting checks & cross-validation.

Results

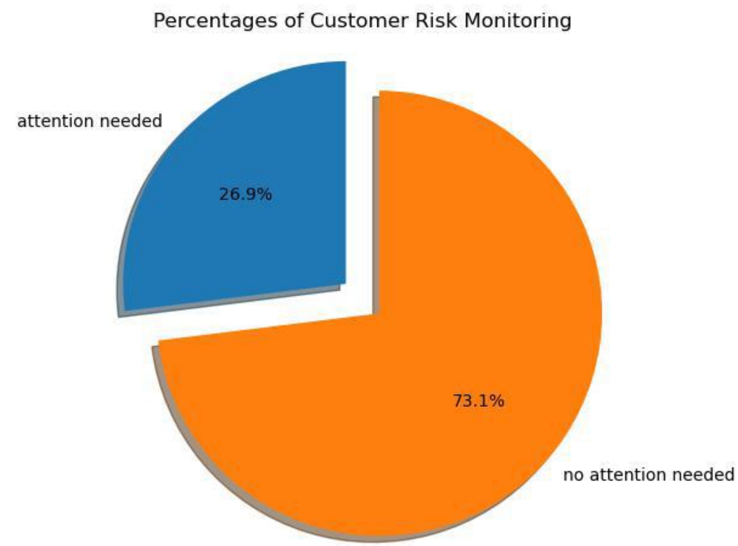
- Logistic Regression delivered interpretable & reliable performance.
- Correlation & VIF analysis improved model stability.
- Class imbalance flagged as challenge; mitigation strategies in place.
- Cross-validation confirmed generalizability with F1 score at ~81% & minimized overfitting.
- Future work: Test advanced models (MLP, RF, XGBoost) for incremental gains.

Risk Prediction empowers proactive customer monitoring & informed decision-making.

Risk Level Insights (EDA)

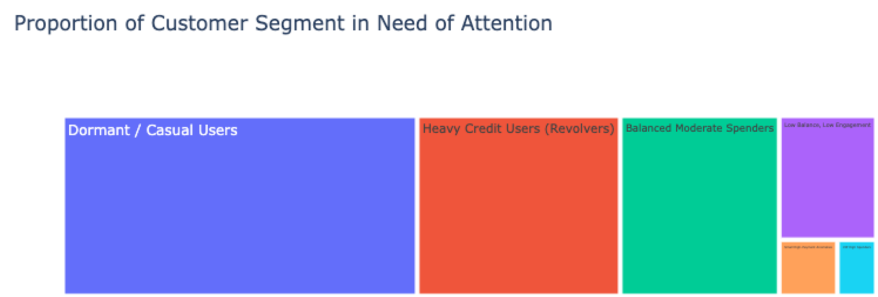
⚙️ **Methodologies**

- 📊 Conducted EDA using stress scores, attention indicators & customer segments.
- 🔍 Quantified proportion of customers needing attention (~26.9%).
- 👥 Segmented at-risk customers: Dormant/Casual, Heavy Credit Users, Moderate Spenders.
- 🗂️ Used tree maps to visualize risk distribution.
- ✅ Identified conversion opportunities & risk control measures.



📈 **Results**

- 🔷 ~26.9% (2,412 out of 8,950) of customers need attention.
- 🔷 Dormant/Casual Users (~44%): Low engagement, re-engagement potential.
- 🔷 Heavy Credit Users (~25%): Profitable but high-risk; repayment & coaching programs.
- 🔷 Balanced Moderate Spenders (~20%): Predictable spenders with upgrade potential.
- ✨ Recommendations: Balance growth with risk management in targeted strategies.



✨ *Risk-level EDA highlights priority groups for engagement, conversion, and proactive risk control.*

RECOMMENDATIONS & NEXT STEPS

Recommendations & Business Impact

💡 Key Recommendations

- 🚨 Implement predictive risk detection model → Prevent ~$7.5M potential losses.
- 🎯 Prioritize at-risk customer segments for conversion campaigns:
  - Dormant / Casual Users (44%) – Re-engage via rewards, offers, gamification.
  - Balanced Moderate Spenders (20%) – Upsell premium/lifestyle products.
  - Heavy Credit Users (25%) – Retain revenue, reduce risk with debt tools & coaching.
  - 📈 Conversion strategies → Move risky customers into high-value, low-risk segments.
- ✅ Next Steps:
  - Launch tailored campaigns per segment with A/B testing.
  - Track migration quarterly with segmentation model.
  - Measure ROI → Spend uplift, repayment improvements, reduced delinquency.

✨ *Turning risk detection into business impact: prevention, engagement, and growth.*

Executive Closing

✨ **This framework enables ABC Bank to:**

- 🛡️ Prevent ~$7.5M in potential annual losses through early risk detection.
- 🚀 Convert at-risk customers into profitable, long-term relationships.
- 📈 Strengthen sustainable growth while maintaining portfolio resilience.

✨ *Linking customer risk management directly to profitability and growth.*