Customer Churn Prediction and Survival Analysis in the Banking Sector

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Abstract

Customer retention has emerged as a strategic priority for banks amid intensifying competition, shrinking margins, and rising digital expectations. Using 10,000 retail-banking records, this study integrates exploratory analysis, survival modeling, and machine learning to explain and predict churn. Building on prior survival-analysis work, this study quantifies risk factors, estimates time to churn, and delivers a Random Forest classifier with 85.9% accuracy for proactive risk scoring. Inactivity, product-portfolio imbalance, and lifecycle stage dominate risk; inactive members face 1.88× higher churn. Combining Kaplan–Meier and Cox models with interpretable ensemble methods provides both temporal and probabilistic insights, enabling targeted re-engagement campaigns, lifecycle retention programs, and portfolio optimization.

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1 Introduction

Customer churn, the process by which customers close accounts or cease doing business with a firm, is a critical concern for banks. On average, acquiring a new customer can cost five to seven times more than retaining an existing one (Business Builders Co, 2024), and even modest improvements in retention can yield disproportionate profit increases (Kumar, 2022). For many financial institutions, high churn rates translate into substantial losses in lifetime value. Effective churn management therefore requires not only understanding who leaves and when, but also why they leave and how the bank can intervene.

Using a rich dataset of ten thousand customers made publicly available by Kollipara (2022), this study investigates demographic, behavioral and financial attributes to determine how they contribute to attrition. Survival analysis and machine learning techniques are employed to estimate individual churn probabilities and design targeted retention programs. The analysis identifies predictive factors through exploratory analysis, quantifies time-to-churn patterns using survival models, builds an accurate predictive classifier for proactive risk scoring, validates model performance against alternative algorithms, and translates statistical findings into actionable business recommendations with quantified ROI. The methods and insights presented here demonstrate an integrated approach to analytics-driven customer retention applicable to similar banking contexts.

1.1 Literature Review

Customer retention has emerged as a fundamental business imperative across service industries, driven by the well-established principle that retaining existing customers costs significantly less than acquiring new ones (Business Builders Co, 2024). In banking, this dynamic is particularly pronounced, with customer lifetime values ranging from $2,000 to $4,000 for typical retail banking relationships (Meleis, 2010).

Early approaches to churn management relied on customer relationship management (CRM) systems that operated reactively, identifying problems only after customers had begun to disengage (Singh et al., 2024). The shift toward proactive churn prediction leverages machine learning techniques to identify customers at risk based on demographic, behavioral, and transactional patterns observed before explicit signals of dissatisfaction emerge. Singh et al. (2024) conducted a comprehensive comparative analysis of multiple ML algorithms on the same dataset used in this study, achieving optimal performance with Random Forest (78.3% accuracy, 69.3% sensitivity using SMOTE oversampling) and XGBoost (83.9% accuracy, 60.1% sensitivity). Their findings validated several critical patterns in bank customer behavior, including elevated churn rates among German customers and the optimal retention profile for customers holding exactly two products, patterns that receive independent confirmation in our exploratory analysis.

However, traditional classification approaches, while effective at answering *who* will churn, provide limited insight into *when* churn occurs or how temporal factors contribute to attrition risk. Survival analysis methods, adapted from biostatistics and telecommunications churn studies (Desai, 2023), offer a complementary framework for modeling time-to-event outcomes. Model interpretability has also emerged as a critical requirement for operational deployment, with recent work demonstrating the utility of SHAP (Shapley Additive Explanations) frameworks for explaining black-box predictions in banking contexts (Peng et al., 2023). The translation of predictive insights into actionable business strategy also remains a critical gap in academic churn research (Brito et al., 2024).

This study bridges these gaps by combining survival analysis methodology with comparative ML evaluation and strategic business planning. The analysis extends the findings of Singh et al. (2024) through several methodological contributions: (1) incorporation of Kaplan-Meier survival curves and Cox modeling to quantify temporal churn patterns; (2) systematic comparison of SMOTE oversampling versus class-weight balancing strategies; (3) application of SHAP values and partial dependence plots for granular model interpretability; and (4) translation of statistical findings into quantified ROI projections and phased implementation strategies.

2 Methods

2.1 Dataset and Pre-Processing

2.1.1 Data Source and Structure

The analysis uses the *Bank Customer Churn* dataset compiled by Kollipara (2022). The dataset comprises 10,000 anonymised records of retail banking customers. Each record includes demographic variables (e.g. gender, geography, age), behavioral indicators (active membership status, tenure), product usage metrics (number of products, credit card ownership), financial variables (balance, estimated salary, credit score) and experiential measures (satisfaction score, complaint status, card type and loyalty points). In addition to the feature columns, the dataset includes a binary target variable indicating whether the customer exited the bank. The data card provided by the dataset author notes that identifier columns such as RowNumber and CustomerId have no predictive value and should be dropped.

2.1.2 Cleaning and Feature Engineering

Prior to analysis, records with missing or duplicate values were removed. Exploratory inspection of the variables revealed no missing values and thus no imputation was required. Identifier fields were discarded, leaving fifteen explanatory variables. An age_group feature was engineered by discretising the Age variable into six categories (18–30, 31–40, 41–50, 51–60, 61–70, 70+) to capture non-linear lifecycle effects while preserving interpretability. One-hot encoding was applied to categorical variables (gender and geography), and the complaint indicator was intentionally excluded from predictive models because it is a lagging indicator of churn: nearly every customer who filed a complaint ultimately left the bank. Continuous variables were standardised to facilitate model training.

2.1.3 Feature Selection and Rationale

Linear correlation analysis with churn revealed distinct tiers of predictive strength (Figure 1). Age, activity status and balance showed moderate to strong correlations (r=0.285, -0.156

and 0.119 respectively) and were retained as core predictors, along with geography and number of products. In contrast, satisfaction_score, point_earned, estimated_salary, credit_score, tenure and card_type exhibited minimal linear relationships (—r— < 0.10) and were excluded from modeling. This selective approach balances predictive power with interpretability, emphasizing modifiable factors (number of products, activity status) and strong demographic predictors (age, geography) that directly inform intervention strategies.

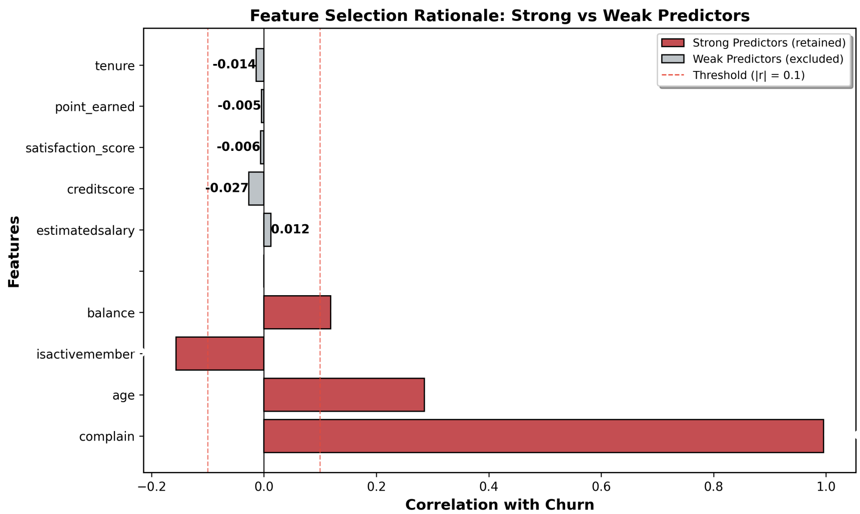


Figure 1: Feature selection rationale comparing strong (—r— ≥ 0.10) and weak (—r— < 0.10) predictors. Strong predictors (red) were retained for modeling; weak predictors (gray) were excluded. Complaint status shows near-perfect correlation (r=0.996) but is excluded as a lagging indicator.

While including complaint status would yield near-perfect accuracy (99%+), it represents a methodological degenerate case: the model achieves inflated performance by relying on a single dominant feature that essentially solves the classification problem before meaningful pattern recognition occurs. Following best practices in operational ML (Kumar, 2022), complaint status was intentionally excluded to enable genuine feature discovery and actionable business intelligence. This trade-off sacrifices headline accuracy metrics (85.9% vs. potential 99%+) to uncover meaningful antecedent patterns that drive real intervention strategies. Models achieving high accuracy through lagging indicators identify customers who have already expressed dissatisfaction through formal channels, exactly when retention is least likely to succeed.

Kernel density estimates for excluded continuous features (Figure 2) confirm their lack of discriminatory power through near-complete distributional overlap between churned and retained customers. Similar minimal effects were observed for categorical excluded features: card type exhibited only a 2.5 percentage point difference in churn rates across all four tiers (19.3%–21.8%). Notably, the number of products showed weak linear correlation (r=-0.048) but was retained based on its demonstrated non-linear U-shaped effect. This feature selection framework maintains predictive power through tree-based algorithms capable of capturing non-linear relationships while prioritizing interpretability.

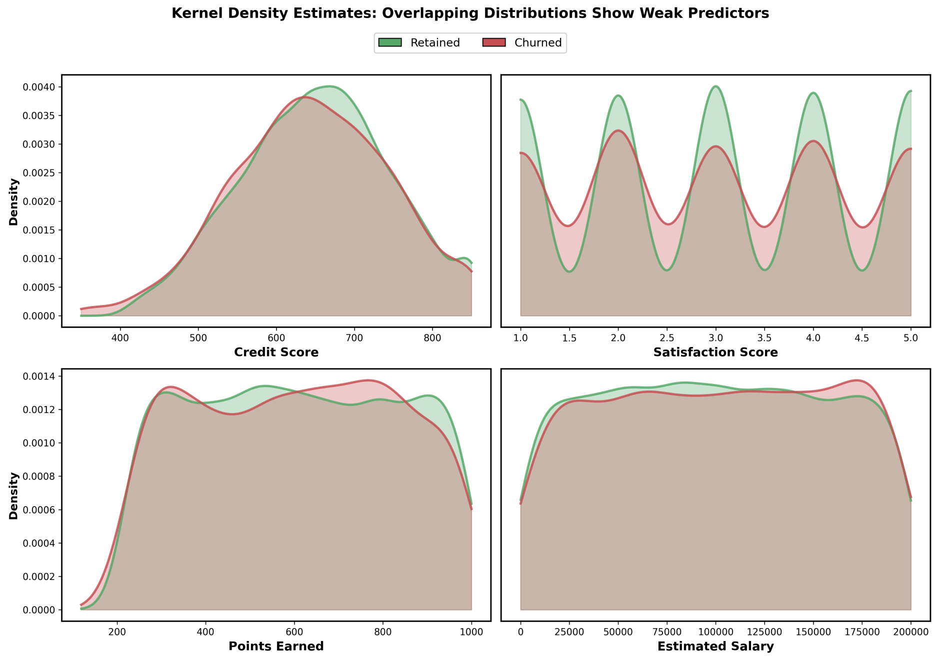


Figure 2: Kernel density estimates for excluded continuous features. Near-complete overlap between churned (red) and retained (green) distributions confirms these features lack discriminatory power, visually validating their weak correlation values.

2.2 Exploratory Data Analysis

2.2.1 Churn Rate and Segment Distributions

The baseline churn rate in the dataset is 20.4 %, corresponding to 2,038 customers exiting during the observation window and 7,962 remaining. Figure 3 illustrates the overall churn distribution. Preliminary univariate analyses identified several striking patterns. The most dominant factor was complaint status: 99.5 % of customers who lodged a complaint subsequently churned, compared to only 0.05 % of non-complainers. Because complaint status is effectively a point of no return, it was analysed separately from the main predictive model.

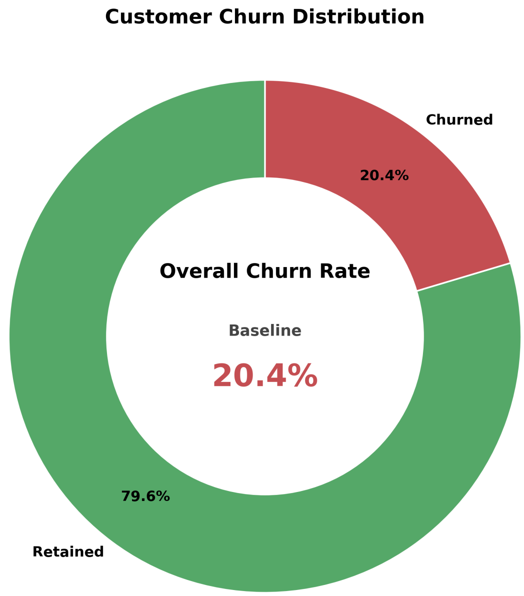


Figure 3: Overall customer churn rate distribution. Baseline churn rate is 20.4%.

A "Goldilocks" effect was observed with respect to the number of products owned: referring to the fairy tale where optimal conditions are found between extremes, customers with exactly two products exhibited the lowest churn rate (7.6 %, n=4,590), whereas those with three or four products showed higher attrition rates (82.7 % and 100 % respectively), as shown in Figure 4. However, the interpretation of extreme churn rates for three and four products must be tempered by small sample sizes (n=266 and n=60 respectively); these figures may reflect sampling variability or unobserved confounding factors rather than a causal effect of product overload. Age displayed a lifecycle pattern, with churn rates rising sharply for pre-retirement customers (51–60 years) and declining for very young or very old clients (Figure 5). Activity status was strongly predictive: inactive members were 1.88 times more likely to churn than active members (Figure 6). Finally, geography revealed a pronounced disparity: German customers had twice the churn rate of their French and Spanish counterparts, suggesting potential market-specific issues (Figure 7).

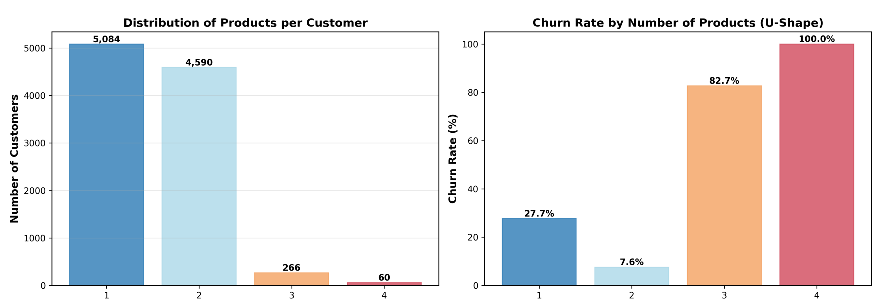


Figure 4: Product count analysis revealing "Goldilocks" effect. Customers with exactly 2 products show optimal retention.

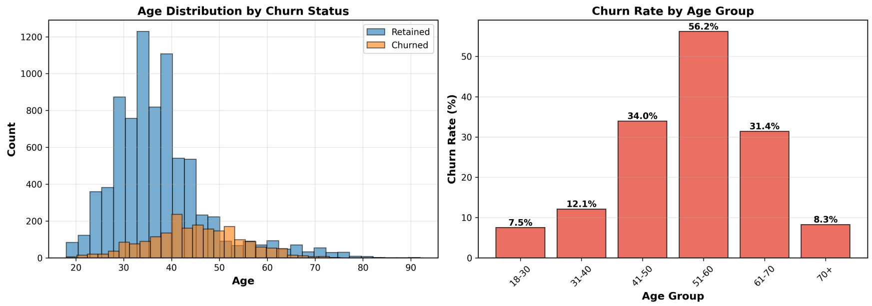


Figure 5: Age lifecycle pattern in churn risk. Peak vulnerability occurs at 51–60 years.

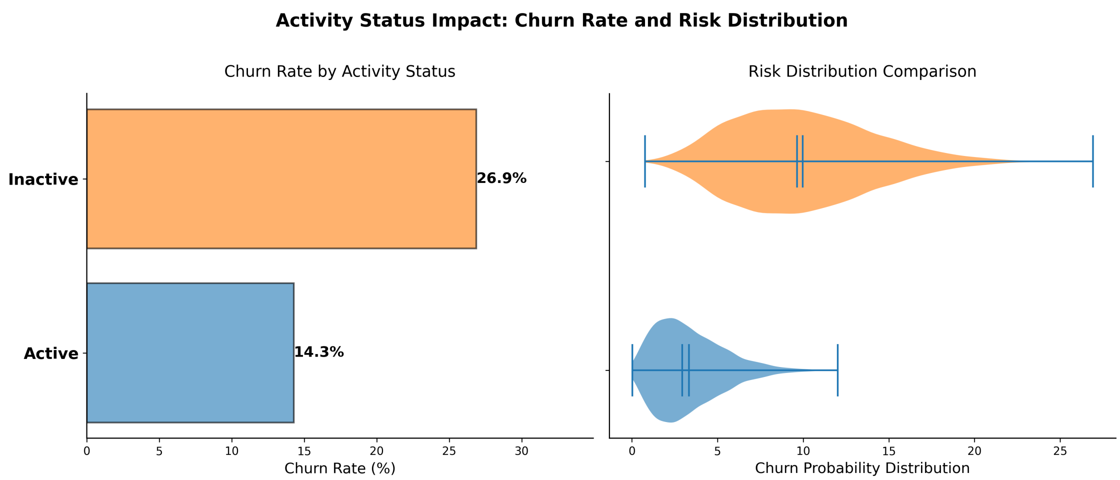


Figure 6: Activity status impact on churn risk. Inactive members exhibit 1.88× higher churn risk than active members.

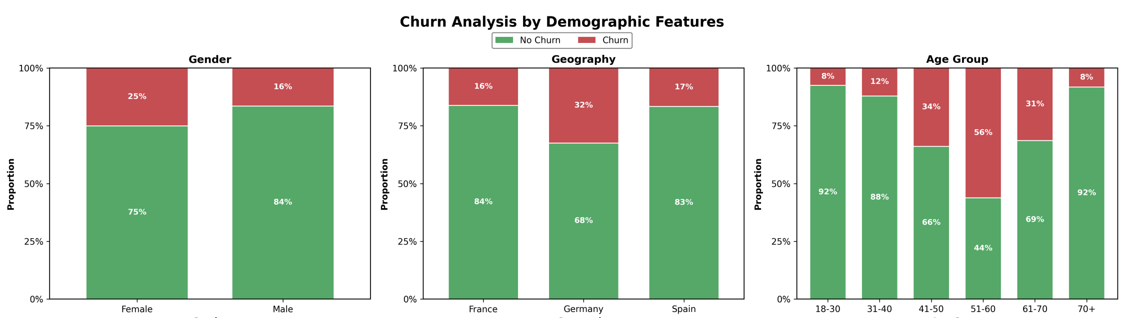


Figure 7: Demographic overview showing geographic churn disparity. Germany exhibits churn rates 2× higher than France and Spain.

2.2.2 Correlation and Interaction Analysis

Pearson correlation and chi-squared tests were used to quantify associations between features and churn. Complaint status exhibited an almost perfect correlation with churn ($r = 0.996$). Age, number of products and activity status had moderate correlations, while balance and tenure showed weaker associations. Correlation analysis (Figure 8) revealed non-linear patterns, particularly for the number of products (a U-shaped relationship) and complex associations between age and activity status. To capture these patterns, later modelling stages employed algorithms capable of handling non-linearities.

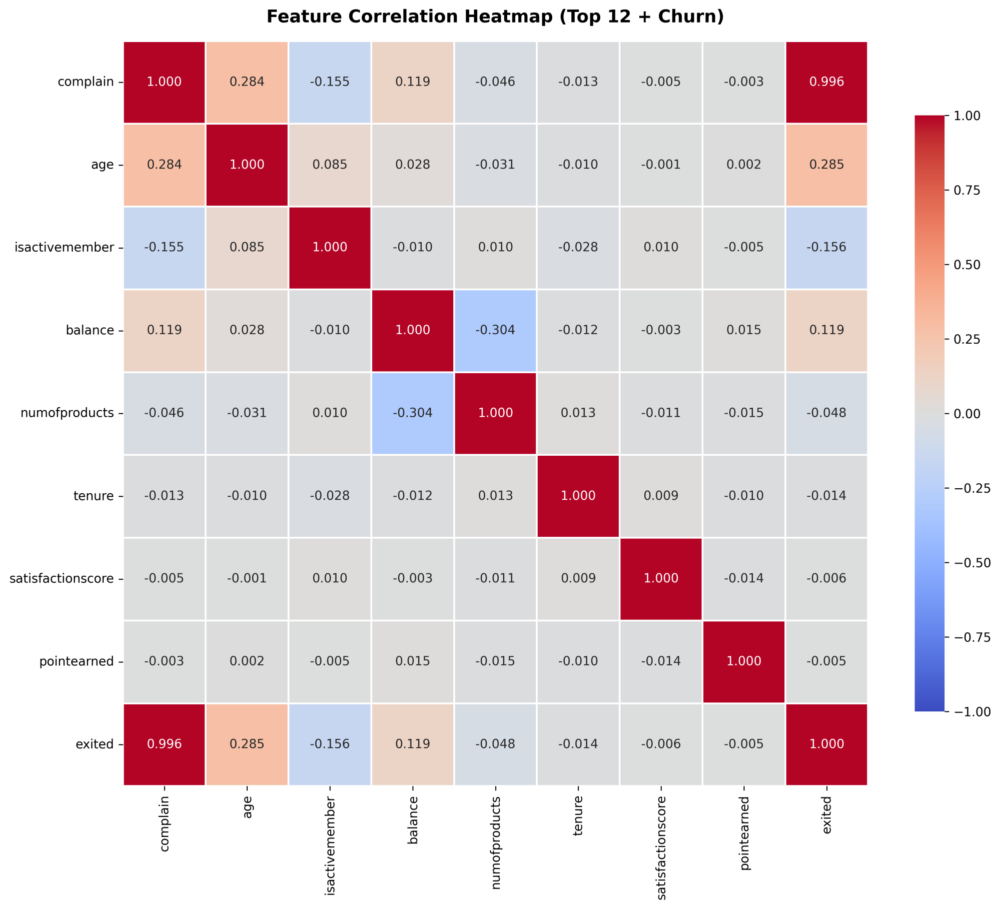


Figure 8: Feature correlation heatmap. Complaint status shows near-perfect correlation with churn (r=0.996). Moderate correlations exist for age, number of products, and activity status.

2.3 Survival Analysis

Survival analysis models the time until an event occurs and is well suited for churn studies where the timing of attrition matters. The fundamental quantity is the survival function $S(t) = \Pr(T > t)$, which represents the probability of surviving at least to time t. The hazard function $h(t)$ quantifies the instantaneous risk of experiencing the event at time t, given survival until t.

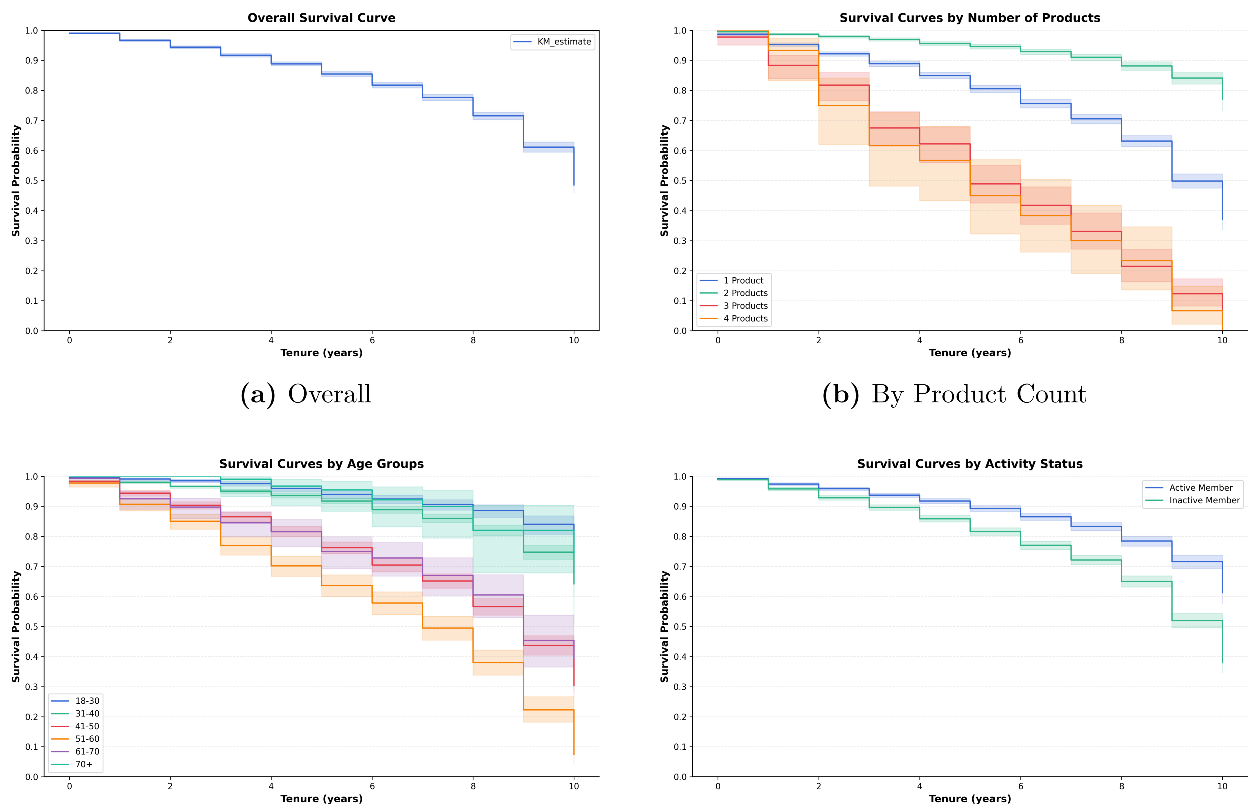
Two complementary techniques were employed: Kaplan–Meier estimators and the Cox proportional-hazards model. The Kaplan–Meier (K–M) estimator, first described by Dudley et al. (2016), is a non-parametric method that estimates the survival function based solely on observed event times and censoring. It is univariate and describes survival according to a single factor. In contrast, the Cox model is a multivariable regression that relates the hazard of the event to multiple covariates simultaneously. As Kassambara (2020) note, the

Cox model accommodates both categorical and quantitative predictors and extends K–M methods by allowing several risk factors to be assessed together. The hazard function in the Cox model is specified as

$$h(t) = h_0(t)\exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p),$$

where $h_0(t)$ is the baseline hazard and the coefficients β_i quantify the effect of covariate x_i on the hazard. Hazard ratios ($\exp(\beta_i)$) greater than one indicate increased risk, while ratios below one signify protective effects.

2.3.1 Kaplan–Meier Results



(a) Overall

(b) By Product Count

(c) By Age Groups

(d) By Activity Status

Figure 9: Kaplan-Meier survival curves across customer segments. (a) Overall survival exceeds 10-year observation window. (b) Product count exhibits U-shaped pattern with 2 products optimal. (c) Age groups show peak vulnerability at 51–60 years. (d) Active members maintain higher retention than inactive members. All differences are statistically significant (p $<$ 0.001).

Kaplan–Meier curves were computed for various customer segments. The overall survival curve (Figure 9a) indicated that median customer lifetime (time until exit) exceeded the 10-year observation window for the majority of customers. When stratified by complaint status, the curves diverged catastrophically: complainers' survival probability dropped to nearly zero almost immediately after the complaint, whereas non-complainers retained high survival throughout the period. Survival curves by number of products (Figure 9b) confirmed the U-shaped pattern; customers with two products had the highest survival, while those with three or four products experienced steep declines. Age group curves (Figure 9c) revealed that pre-retirement customers (51–60) had the steepest decline, consistent with the lifecycle hypothesis. Activity status curves (Figure 9d) showed that active members maintained higher survival probabilities over time. Log-rank tests confirmed that these differences were statistically significant. Table 1 summarizes the complete log-rank test results for all customer segment comparisons, confirming that all features exhibited highly significant differences in survival distributions ($p < 0.001$).

Table 1: Log-rank test results comparing survival distributions across customer segments. All features exhibit highly significant differences ($p < 0.001$).

Feature	**Test Statistic**	**p-value**
Age Group	1124.09	< 0.001
Number of Products	1243.64	< 0.001
Activity Status	179.24	< 0.001
Geography	243.70	< 0.001
Gender	100.47	< 0.001
Balance Group	154.37	< 0.001

The cumulative hazard function $H(t) = -\ln(S(t))$ provides a complementary perspective to survival curves by quantifying the accumulated risk of churn over time. While survival curves show the probability of retention, cumulative hazard directly measures the compounding risk of exit. The cumulative hazard plot (Figure 10) illustrates that churn risk accumulates gradually in the early years but accelerates markedly after approximately 7–8 years of tenure, indicating a critical intervention window. This pattern suggests that long-tenured customers who have accumulated substantial hazard may require intensified retention efforts, even if their current survival probability remains relatively high.

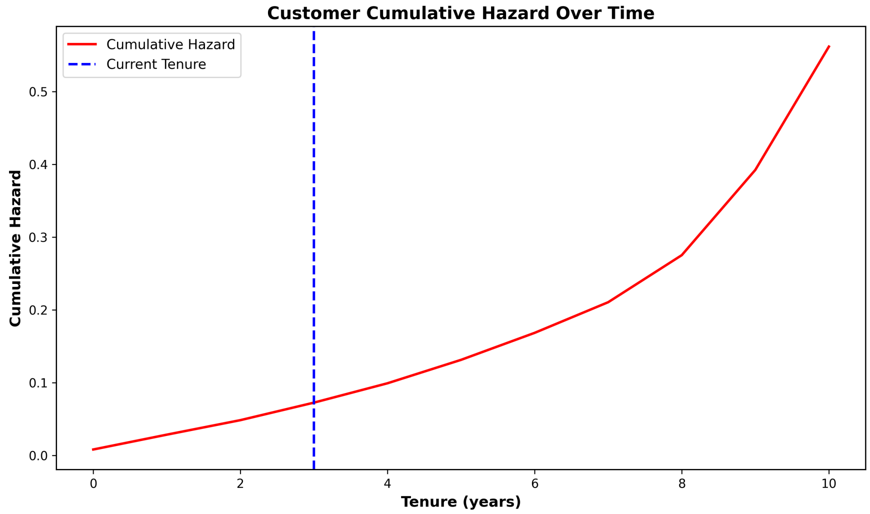


Figure 10: Cumulative hazard function for representative customer with 3 years tenure. Accelerating hazard rate after 7–8 years identifies critical intervention window for long-tenured customers.

2.3.2 Cox Model Results

A Cox proportional-hazards model was fitted excluding the complaint variable (to avoid its dominance). Covariates included gender, tenure, balance, number of products, activity status, geography and age group dummies. The model achieved a concordance index (C-index) of 0.74, indicating good discriminative power. Hazard ratios quantified the relative risk associated with each feature (Table 2). Notably, the age 51–60 group had a hazard ratio of 7.94, meaning their risk of churn was nearly eight times that of the baseline 18–30 group. Being an active member reduced the hazard by 46 % (hazard ratio 0.54), while German nationality increased the hazard by 60 % relative to France. The number of products exhibited a linear hazard ratio close to one per additional product, but this masked the underlying U-shape seen in the K–M curves.

Table 2: Cox Proportional Hazards Model Results (excluding complaint status). Concordance Index (C-index): 0.74. Baseline age group: 18-30. Baseline geography: France. HR > 1 indicates increased churn risk; HR < 1 indicates protective effect.

Feature	Hazard Ratio	p-value
Age Groups (vs. 18-30)		
31-40	1.15	0.341
41-50	2.45	0.001
51-60	7.94	<0.001
61-70	4.23	<0.001
70+	2.89	0.002
Other Features		
Gender (Female)	1.47	<0.001
IsActiveMember	0.54	<0.001
Geography (Germany)	1.60	<0.001
Geography (Spain)	0.93	0.483
NumOfProducts	1.02	0.671
Balance	1.00	0.052
Tenure	0.99	0.156

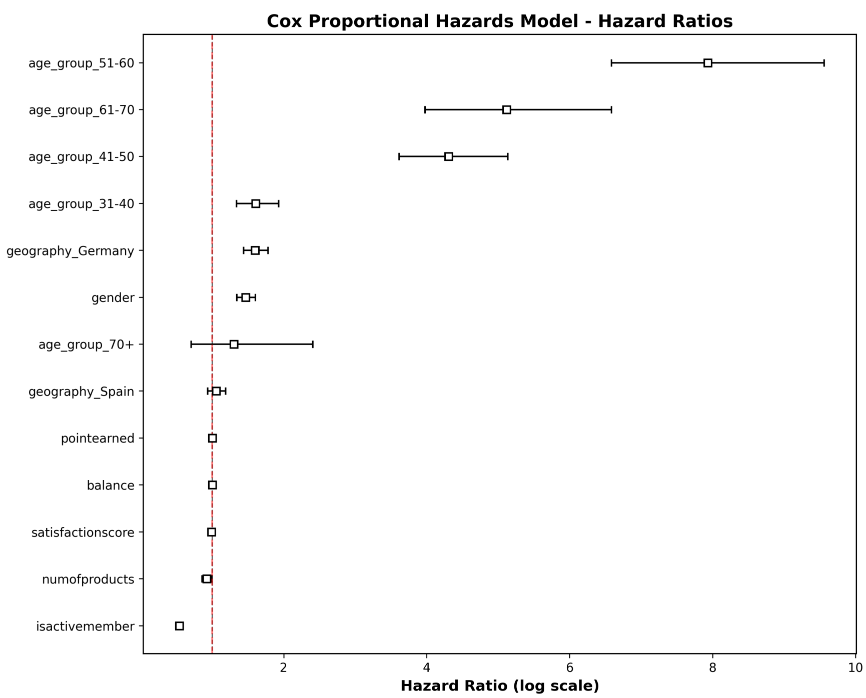


Figure 11: Cox Proportional Hazards model coefficients. Hazard ratios quantify relative churn risk for each feature.

2.4 Predictive Modelling

2.4.1 Random Forest Classifier

To identify at-risk customers before a complaint is lodged, a random forest classifier was trained on the curated feature set. Random forests are ensemble learning techniques that combine the output of many decision trees built on bootstrap samples of the data. Each tree considers a random subset of features at each split and contributes a vote to the final prediction. This majority-voting scheme improves accuracy and reduces overfitting (GeeksforGeeks, 2025). Formally, for a random forest with B trees, the ensemble prediction is

$$\hat{f}_{\mathrm{RF}}(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^{B} \hat{f}_b(\mathbf{x}),$$

where $\hat{f}_b(\mathbf{x})$ is the prediction from the b-th tree trained on a bootstrap sample with random feature selection at each split. For classification, the final prediction is the majority vote across all trees.

An extensive four-stage grid search was performed to tune hyperparameters such as the number of trees, maximum depth, splitting criteria, minimum samples per split and class weights. Class imbalance (20.4 % churn) was addressed by weighting the minority class twice as heavily as the majority class. The optimal configuration consisted of 900 trees, maximum depth of 11, Gini impurity criterion, no feature subsetting (max_features=None), minimum split size of four samples and class weight ratio $\{0 : 1, 1 : 2\}$.

2.4.2 Model Comparison

To ensure robustness, the Random Forest classifier was compared against two gradient-boosting alternatives: XGBoost (Chen and Guestrin, 2016) and LightGBM (Ke et al., 2017). Both are ensemble methods that sequentially add weak learners to correct prior errors, differing primarily in their splitting strategies: XGBoost uses a level-wise (breadth-first) tree growth approach with regularization, while LightGBM employs a leaf-wise (depth-first) growth strategy optimized for computational efficiency. All models were trained on identical data splits and tuned with analogous hyperparameter grid searches. Performance comparisons are presented in Section 4.1.

3 Results

3.1 Model Performance

The Random Forest model achieved 85.9 % accuracy on the 2,000-sample test set, representing a 6.3 percentage point improvement over the majority-class baseline (79.6 %) and demonstrating successful discrimination of churn risk. Class-specific performance metrics (Table 3) showed precision of 68.0 %, recall of 57.8 % and F1-score of 62.5 %, with the most pronounced improvement over the untuned baseline being recall (+21 percentage points).

Table 3: Model performance metrics summary. Test set contains 2,000 samples with 20.4% churn rate. Model correctly identified 236 of 408 churners (57.8% recall).

Metric	Value	Interpretation
Accuracy	85.9%	Share of decisions correct; sensitive to class imbalance.
Precision	68.0%	Fraction of flagged churners that actually churn; drives retention efficiency.
Recall	57.8%	Fraction of actual churners caught; primary lever for reducing missed churn.
F1-Score	62.5%	Balance of precision/recall; single-number summary under asymmetric costs.
ROC-AUC	0.858	Probability model ranks churner above non-churner; threshold-agnostic.
PR-AUC	0.712	Average precision across recalls; more informative under class imbalance.

Receiver-operating characteristic (ROC) curves yielded an area under the curve (AUC) of 0.858, indicating strong threshold-agnostic discrimination between churners and non-churners. The classifier achieves a lower PR-AUC of 0.712 compared to ROC-AUC, reflecting the inherent challenge of maintaining high precision under class imbalance (20.4 % churn rate). The confusion matrix (Table 4) shows the model correctly identified 236 of 408 churners at the chosen decision threshold; 172 churners were missed, while 111 non-churners were incorrectly flagged as churn risks.

Table 4: Confusion matrix showing model predictions versus actual outcomes. Model correctly identified 236 churners while missing 172.

	Predicted: Retained	**Predicted: Churned**
Actual: Retained	1,481 (TN)	111 (FP)
Actual: Churned	172 (FN)	236 (TP)

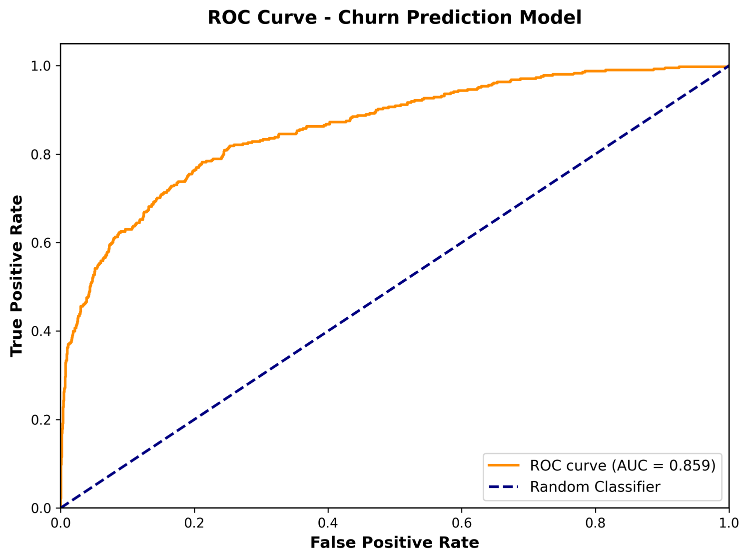


Figure 12: ROC curve demonstrating model discriminative power. Area under curve (AUC) equals 0.858.

The ROC-AUC quantifies the probability that the classifier ranks a randomly chosen positive instance higher than a randomly chosen negative instance, while PR-AUC measures average precision across all recall thresholds.

Feature importance was assessed using built-in impurity measures, permutation importance and SHAP (Shapley Additive Explanations) values (Figure 13). Permutation importance measures the decrease in model performance when a feature is randomly shuffled:

$$I_j = \mathbb{E}[L(y, f(\mathbf{x}_{\mathrm{perm}(j)}))] - \mathbb{E}[L(y, f(\mathbf{x}))],$$

where $\mathbf{x}_{\mathrm{perm}(j)}$ denotes the feature vector with the j-th feature randomly permuted, and L is the loss function. SHAP values provide a unified framework for feature attribution based on Shapley values from cooperative game theory, quantifying each feature's marginal contribution to individual predictions. Age and the number of products emerged as the most influential predictors: age contributed the largest SHAP impact on individual predictions, while the number of products showed the highest permutation importance. Activity status, balance and German nationality were important but secondary drivers. Partial dependence analysis (Figure 14) confirmed the near-monotonic increase in churn probability with age up to the 51–60 group, while exploratory data analysis (Section 2) revealed the U-shaped effect of the number of products.

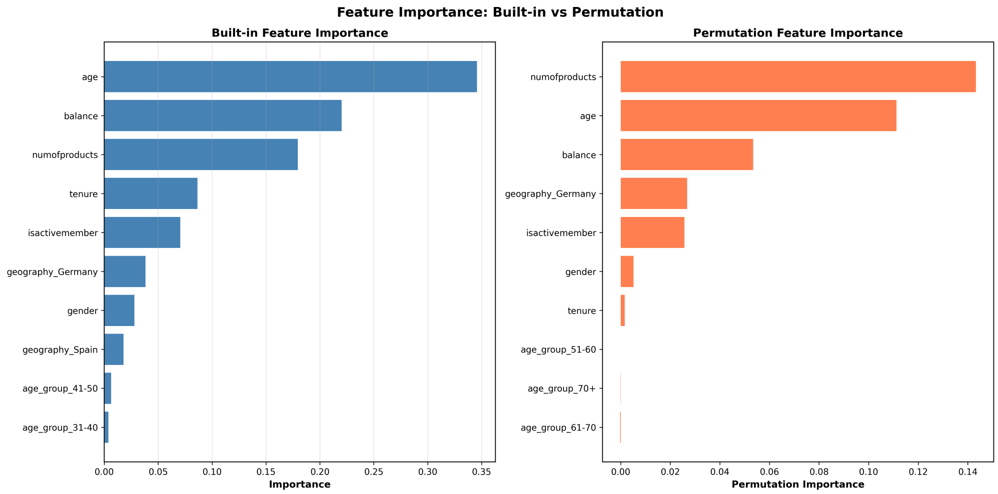


Figure 13: Feature importance comparison using impurity measures, permutation importance, and SHAP values. Age and number of products emerge as most influential predictors.

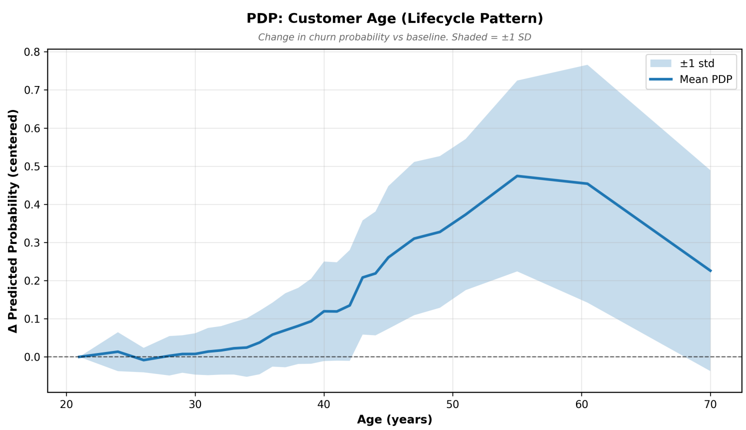


Figure 14: Partial dependence plot for age. Near-monotonic increase in churn probability peaks at 51–60 years.

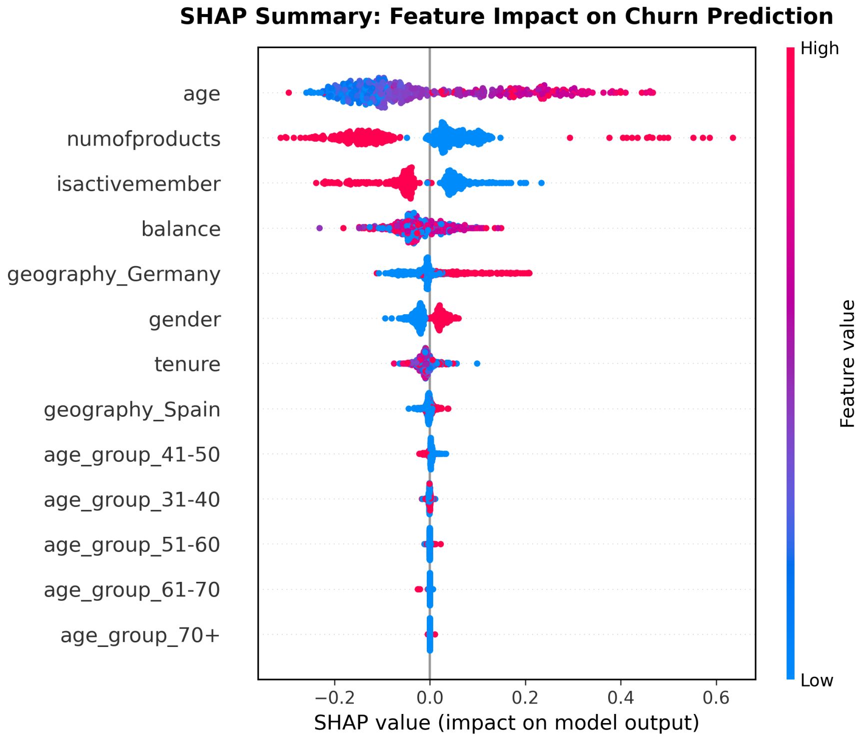


Figure 15: SHAP summary plot showing feature contributions across all predictions. Blue bars indicate protective effects; red bars indicate increased churn risk.

The SHAP summary plot provides a population-level view of feature contributions across all customers. To illustrate how SHAP values decompose an individual prediction into feature-level contributions, Figure 16 presents a waterfall plot for a specific customer (Customer #0). This example demonstrates how the model's prediction is constructed step-by-step, starting from the average baseline prediction and sequentially adding or subtracting the contribution of each feature. For this customer, the low age (26 years) provides the largest protective effect (reducing churn risk by 0.145), followed by active membership status (-0.054) and high account balance (-0.037). The only risk-increasing factor is the customer's single product ownership (+0.020). These feature-level contributions sum to a final predicted probability of 7.18%, indicating low churn risk. This customer was correctly predicted as retained, demonstrating the model's ability to identify low-risk profiles.

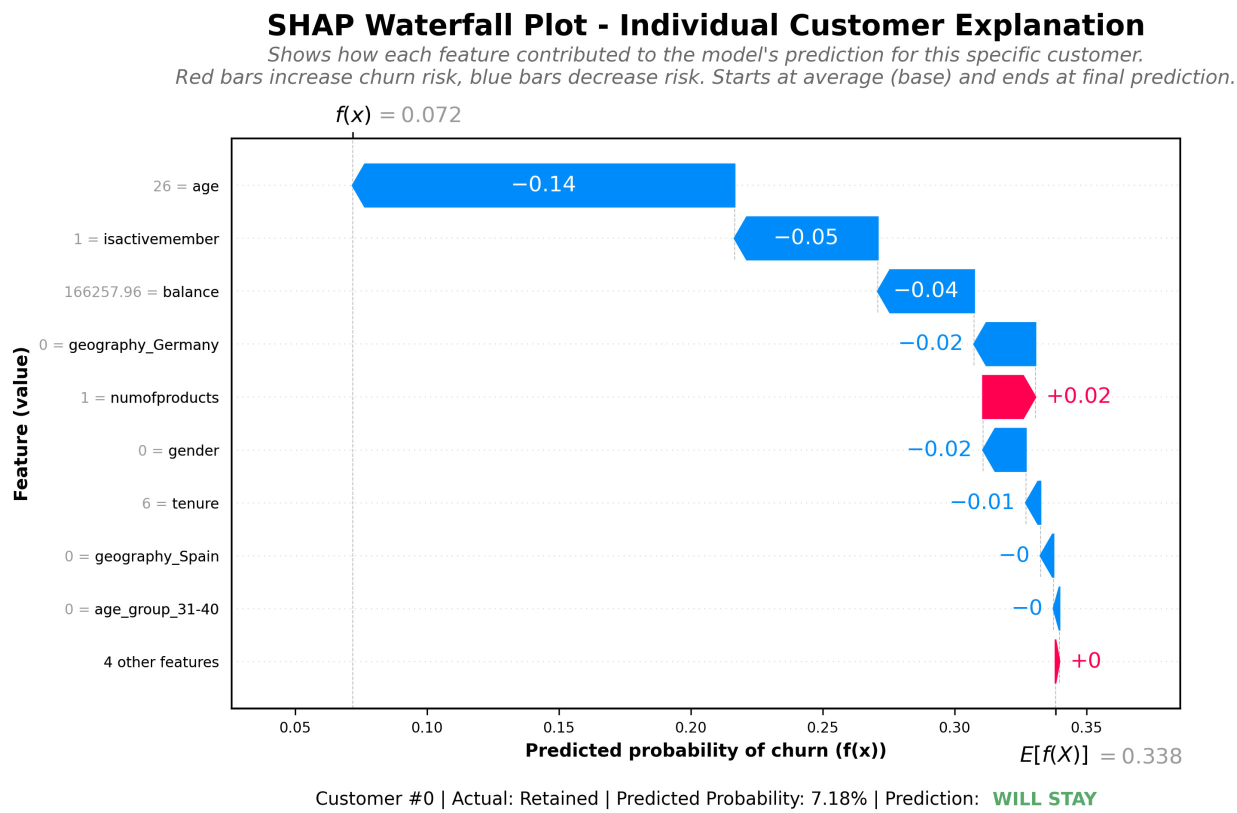


Figure 16: SHAP waterfall plot for individual customer prediction. Each feature's contribution appears as colored bars: blue decreases risk, red increases risk. Prediction evolves from baseline average to final probability.

Table 5: Top 5 Contributing Features for Customer #0. Features are ranked by absolute SHAP value, with positive values indicating increased churn risk and negative values indicating decreased risk. This customer was correctly predicted as retained with a 7.18% churn probability.

Feature	**Value**	**SHAP**	**Impact**
Age	26.00	-0.145	Decreases
IsActiveMember	1.00	-0.054	Decreases
Balance	166,257.96	-0.037	Decreases
Geography_Germany	0.00	-0.023	Decreases
NumOfProducts	1.00	+0.020	Increases

3.2 Model Validation

To ensure robustness, the random forest was compared against two gradient-boosting alternatives: XGBoost and LightGBM (Figure 17). All models were trained on identical splits and tuned with analogous hyperparameter searches. Random forests slightly outperformed the alternatives in F1-score (62.5 % vs. 60.5–61.0 %) and demonstrated more stable generalisation across folds. A comprehensive metrics comparison (Figure 18) confirmed Random

Forest's superiority. Experiments evaluating synthetic minority oversampling (SMOTE) versus class weighting (Figure 19) revealed that SMOTE increased recall at the expense of a substantial rise in false positives; class weights offered a more balanced trade-off. Additional engineered features (interaction terms and polynomial expansions) did not improve performance, underscoring that tree-based methods inherently capture non-linear interactions.

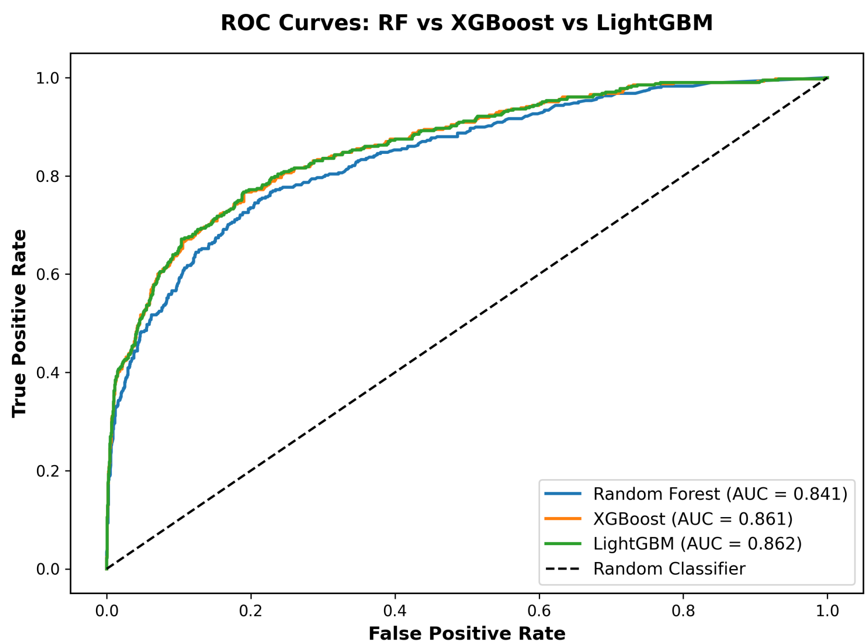


Figure 17: ROC curve comparison across three algorithms. Random Forest achieves highest discriminative power (AUC = 0.858).

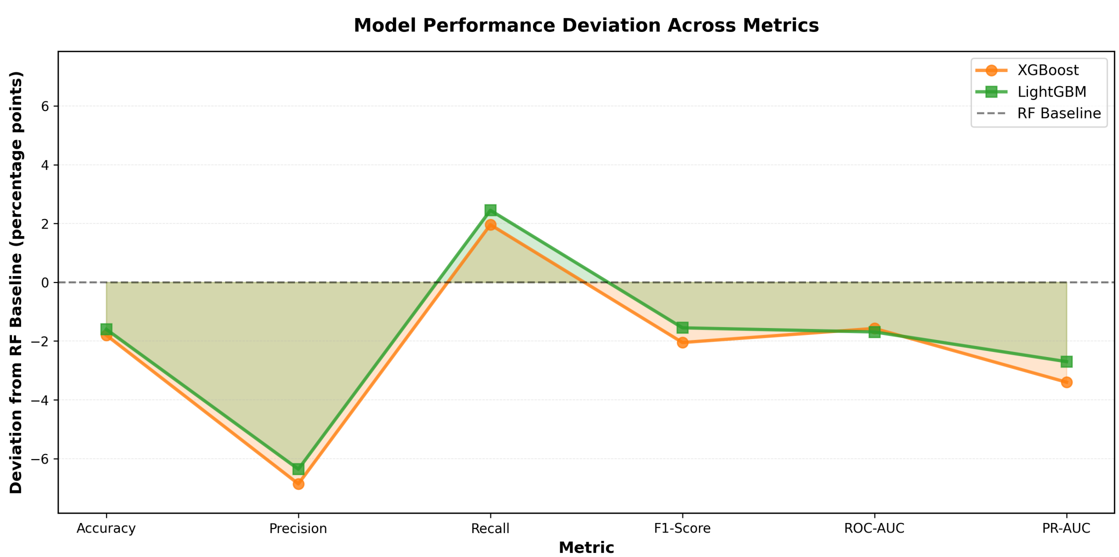


Figure 18: Model performance deviation from Random Forest baseline. Both XGBoost and LightGBM underperform across most metrics.

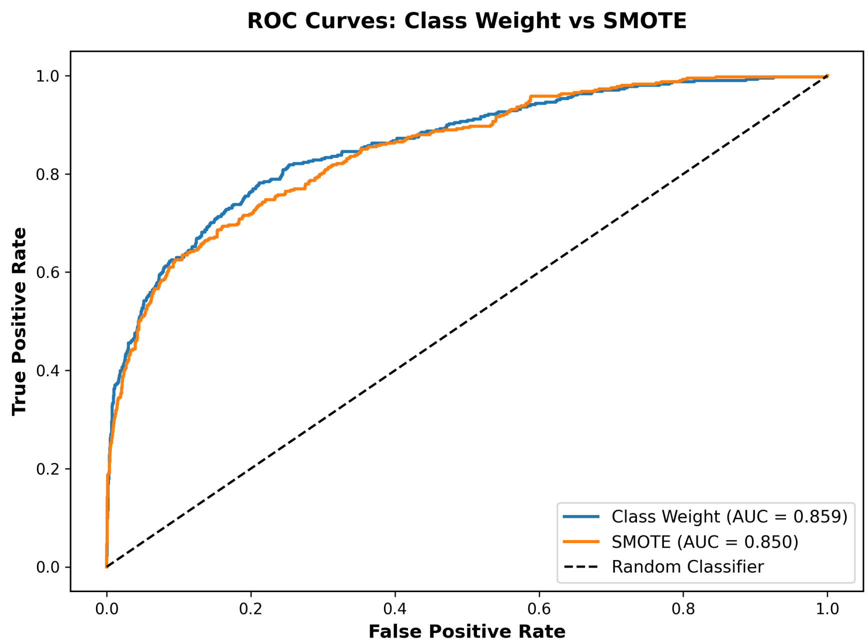


Figure 19: SMOTE versus class weight ROC comparison. SMOTE increases recall at the expense of higher false positive rate.

4 Discussion

4.1 Key Findings

The combined analyses yielded several actionable insights:

1. **Lifecycle stage drives churn risk.** Age exhibited a strong non-linear effect, with the 51–60 cohort showing a hazard ratio of 7.94 relative to the youngest group. This demographic corresponds to pre-retirement customers who may consolidate assets or seek better retirement products elsewhere. Specialized retention programs focusing on retirement planning and personalised services are warranted.

2. **Customer engagement level is the strongest modifiable predictor.** Customers with frequent engagement exhibit a 46 % reduction in churn hazard relative to less engaged customers. Re-engagement campaigns targeting inactive customers (through personalised communications, gamification and incentives) represent a promising lever for retention.

3. **Geography matters.** German customers exhibited twice the churn rate of French and Spanish customers and a hazard ratio of 1.60. Market-specific issues such as competition, regulation or service quality likely underlie this disparity and require targeted investigation and localisation strategies.

4. **Product portfolio has a Goldilocks zone.** Customers with two products displayed the lowest churn (7.6 %, n=4,590), whereas those with three or four products showed

substantially higher attrition (82.7 % and 100 % respectively, with small sample sizes n=266 and n=60). The pattern suggests that optimal cross-selling targets two products; portfolio capping at two products and consolidation strategies for customers with single products could improve retention. Extreme rates for three-plus products should be interpreted cautiously due to limited sample sizes.

5. **Complaint status creates a trivial prediction problem through extreme feature imbalance.** Virtually every customer who filed a complaint subsequently exited (99.5% correlation), making complaint status a near-perfect binary separator. Following best practices in operational ML (Kumar, 2022), complaint status was intentionally excluded to enable genuine feature discovery and actionable business intelligence. This trade-off sacrifices headline accuracy metrics (85.9% vs. potential 99%+) to uncover meaningful antecedent patterns that drive real intervention strategies. Complaint prevention and intervention remain critical but require separate monitoring protocols distinct from predictive modeling.

These findings are supported by both the survival model and the random forest classifier, reinforcing the validity of the patterns. Importantly, the risk factors vary in modifiability: age and geography are inherent, whereas number of products and activity status are under managerial control. Effective retention strategies should therefore prioritise modifiable drivers.

4.2 Business Applications and Strategic Implications

4.2.1 Customer Risk Profiles

Using the predicted probabilities from the random forest and SHAP explanations, customers can be segmented into risk tiers (Table 6). **Low-risk** customers are typically 18–40 years old, active, own one or two products and reside in France or Spain; they have churn probabilities below 20 %. **Medium-risk** customers are 40–55, inactive or semi-active, own only one product and have short tenure; their churn probabilities range from 30–60 %. **High-risk** customers are 55–70, inactive, either under-serviced (one product) or potentially over-serviced (three to four products) and often based in Germany; their churn probabilities exceed 70 %. Note that customers with three to four products constitute a small subgroup (n=326) and warrant targeted investigation rather than broad assumptions.

Table 6: Customer risk segmentation and intervention strategies. Risk tiers based on Random Forest predicted probabilities and SHAP attribution. Separate escalation protocol exists for customers who have lodged complaints.

Attribute	Low Risk	Medium Risk	High Risk
Churn Prob.	<20%	30-60%	>70%
Age	18-40	40-55	55-70
Activity Status	Active	Inactive/semi-active	Inactive
Products	1-2 (optimal)	1 (under-served)	1 or 3-4 (over-served)
Geography	France/Spain	Any	Germany
Tenure	Varied	Short	Varied
Recommended Intervention	Nurture with loyalty rewards; encourage second product	Re-activation campaigns; life-stage specific offers; optimize to 2 products	Escalated personal intervention; dedicated RM; portfolio consolidation

For each segment, tailored interventions were developed. Low-risk customers should be nurtured through personalised offers and loyalty rewards to deepen engagement and encourage adoption of a second product. Medium-risk customers benefit from re-activation campaigns, life-stage specific offers and product bundles that optimize their portfolio at two products. High-risk customers require immediate, high-touch intervention: dedicated relationship managers, portfolio consolidation, retirement planning services and enhanced support for German clients. Customers who have already lodged complaints should trigger an escalation protocol separate from the predictive model.

4.2.2 Strategic Recommendations and ROI Analysis

Four priority interventions were proposed and costed (Table 7). Each intervention targets specific at-risk segments identified through the predictive analysis.

Product portfolio management focuses on optimizing customers with one product up to the optimal two-product level, representing 9,674 customers (96.7% of the dataset). Research by Singh et al. (2024) analyzing large bank datasets found that customers with exactly two products showed superior retention compared to single-product customers, suggesting optimal relationship depth. While the dataset shows high churn rates for customers with three to four products (n=326 total), the small sample sizes limit definitive conclusions about this group; targeted investigation rather than broad policy changes is recommended.

Lifecycle retention program launches a pre-retirement engagement program targeting customers aged 50–70, offering complimentary retirement consultations, dedicated relationship managers and premium services. This demographic represents a critical segment, as research indicates customers aged 50–70 control approximately 65% of banking wealth and exhibit strong loyalty when properly served (Marr, 2024). Tailored financial planning services for older adults have been shown to deepen trust and improve retention (National Community Reinvestment Coalition, 2021).

Re-engagement campaign develops a system to monitor inactivity, trigger personalised communications and deliver incentives or gamified challenges to dormant customers. Studies demonstrate that personalized, data-driven engagement campaigns deliver substantially higher ROI (1,344%) compared to standard campaigns (390%) (Cline, 2024), while 66% of banking customers are at risk of attrition due to disengagement (Cornerstone Advisors, 2025).

Germany market localisation conducts root-cause research in Germany and addresses the identified issues through localised products, improved language support and competitive pricing. Multilingual digital banking systems improve customer experience and retention (Hunsicker, 2023), while market-specific competitive pricing directly addresses the service gaps driving attrition (Smith, 2025).

Table 7: Strategic interventions and ROI analysis. Assumes $2,000 average customer lifetime value. Customer impact estimates are semi-illustrative, derived from segment sizes and assumed intervention effectiveness rates: Product Portfolio (25% churn reduction for 1-product customers), Lifecycle (30% reduction for age 50-70), Re-engagement (20% reactivation for inactive members), Germany (40% reduction for German customers). Total reflects unique customers across interventions with overlap adjustments. Year 1 net loss of $215k; Years 2-3 yield annual profit of $320k.

Intervention	**Description**	**Customers Saved**	**Cost**	**Year 1 ROI**
Product Portfolio Management	Cap products at 2; audit consolidation	150	$90k	4.9×
Lifecycle Retention	Pre-retirement engagement; retirement consultations	130	$330k	1.5×
Re-engagement Campaign	Monitor inactivity; personalized comms	100	$230k	0.8×
Germany Localization	Root-cause research; localized products	100	$425k	1.3×
Total	**Combined interventions**	**480**	**$1.175M**	

Assuming a conservative average customer lifetime value of $2,000 (Meleis, 2010), the combined interventions would save approximately 480 customers in the first year, retaining $960k in revenue. Industry research supports this CLV estimate, with Oliver Wyman data indicating traditional banks acquire customers at a cost of $750, resulting in an average lifetime value of $4,500 (Chowdhry, 2019). The $2,000 figure represents a conservative lower bound appropriate for risk assessment.

Total Year 1 investment of $1.175M would lead to a small net loss ($215k), but Years 2 and 3 yield annual profits of $320k as ongoing costs diminish. This aligns with research showing that retention initiatives targeting existing customers yield 70% returns compared to 10% for new-customer initiatives (Browning, 2024). Sensitivity analyses suggest that in optimistic scenarios the churn rate reduction could reach 25 %, whereas pessimistic outcomes might still achieve a 15 % reduction. Given the substantial hidden value in complaint prevention and the relatively low risk of the product cap initiative, a phased implementation beginning with high-ROI actions is recommended.

4.2.3 Implementation Roadmap

An implementation roadmap structures the roll-out over twelve months. **Phase 1 (Weeks 1–4)** focuses on quick wins: enforcing the two-product cap, integrating the predictive model into the customer relationship management system and initiating an audit of complaint drivers. **Phase 2 (Months 2–6)** deploys the re-engagement campaign and pilots the lifecycle program with a subset of pre-retirement customers. **Phase 3 (Months 6–12)** scales the lifecycle program, executes Germany-specific fixes and retrains the model with new data. Continuous monitoring of model performance and retention metrics ensures that interventions can be adjusted dynamically.

4.3 Limitations and Future Research

Several limitations should be acknowledged. First, the dataset spans only a one-month observation window, which may not capture long-term churn patterns or seasonal variations. The temporal scope limits the ability to evaluate interventions over extended periods and may obscure lifecycle trends that unfold over years rather than weeks. Second, the dataset lacks granular transaction data, social-media signals and sentiment indicators that could enhance predictive power. Third, cost estimates for the proposed interventions are derived from industry benchmarks rather than internal bank data; actual implementation costs may vary significantly depending on organizational structure, existing technology infrastructure and market-specific regulatory requirements. Fourth, while the model achieves strong performance metrics, the 57.8% recall rate means that approximately 42% of churners are not identified proactively, representing a potential revenue risk. Fifth, the analysis assumes customers are independent actors; in reality, churn may be influenced by social networks, family accounts or broader economic conditions not captured in the data.

Future research could address these limitations by incorporating longitudinal data spanning multiple years, integrating external data sources (economic indicators, competitive intelligence, market sentiment), conducting pilot studies to validate cost estimates and refine intervention effectiveness, and exploring advanced modeling techniques such as deep learning or ensemble methods that combine survival models with neural networks. Additionally, A/B testing of proposed interventions would provide empirical validation of the recommendations' efficacy in real-world settings.

4.4 Conclusion

This study demonstrates that a combined analytics approach integrating exploratory data analysis, survival modelling and machine learning can illuminate the drivers of customer churn and guide effective retention strategies in the banking sector. The findings confirm that not all customers are equally likely to churn and that demographic, behavioral and product factors interact in complex ways. The random forest classifier provides an operational tool for pre-complaint risk scoring, while the survival model offers interpretable hazard estimates that inform targeted interventions. By implementing the recommended strategies, the bank studied here can materially reduce churn, protect revenue and enhance customer satisfaction. More broadly, the research illustrates how data-driven decision making can transform customer management in financial services.

4.5 Acknowledgements

This analysis builds upon the foundational methodology developed by Archit Desai in his *Customer Survival Analysis and Churn Prediction* project (Desai, 2023). The original repository established the innovative approach of combining survival analysis (Kaplan–Meier estimators, Cox Proportional Hazards regression) with machine learning (Random Forest classification) for predictive churn modeling. While the original project focused on telecom customer churn, this implementation adapts the methodology for banking sector challenges with several enhancements: modular code architecture with standardized utility functions, comprehensive model validation experiments comparing algorithms and techniques, business-focused documentation with ROI projections and implementation roadmaps, and production-ready checkpointing and reproducibility systems. The dataset used in this analysis was sourced from the Bank Customer Churn Dataset on Kaggle (Kollipara, 2022).

References

José Brito, Carlos Brito, Pedro Henriques, and Isabel Ferreira. A framework to improve churn prediction performance in retail banking. *Financial Innovation*, 10(17), 2024. doi: 10.1186/s40854-023-00558-3.

Lance Browning. Lifetime value vs. share of wallet: Which is the right metric for retention?, February 2024. URL `https://thefinancialbrand.com/news/payments-trends/are-banks-using-the-right-metrics-for-customer-retention-175287`.

Business Builders Co. The high cost of neglecting customer retention: Why it's 5x cheaper to keep customers, 2024. URL `https://businessbuildersco.com/post/the-high-cost-of-neglecting-customer-retention`. Accessed 23 October 2025.

Aman Chowdhry. Chime: Digital bank expected to quadruple its revenue this year to $200 million, November 2019. URL `https://pulse2.com/chime-quadruple-revenue-200-million/`. Oliver Wyman: CAC $750; LTV $4,500.

Jeffrey Cline. Four big ideas for banks looking to drive down attrition, October 2024. URL `https://thefinancialbrand.com/news/bank-onboarding/the-churn-challenge-four-big-ideas-for-banks-and-credit-unions-looking-to-drive-down-`

Cornerstone Advisors. The rising challenge: Re-engaging dormant customers, 2025. Webinar summary.

Archit Desai. Customer survival analysis and churn prediction, 2023. URL `https://github.com/archd3sai/Customer-Survival-Analysis-and-Churn-Prediction`. Accessed 23 October 2025.

William N. Dudley, Rita Wickham, and Nicholas Coombs. An introduction to survival statistics: Kaplan–meier analysis. *Journal of the Advanced Practitioner in Oncology*, 7(1): 91–100, 2016. URL `https://pmc.ncbi.nlm.nih.gov/articles/PMC5045282/`. Accessed 23 October 2025.

GeeksforGeeks. Random forest algorithm in machine learning, 2025. URL `https://www.geeksforgeeks.org/machine-learning/random-forest-algorithm-in-machine-learning/`. Accessed 23 October 2025.

Anna Hunsicker. Benefits of a multilingual digital banking system, October 2023. URL `https://www.jackhenry.com/fintalk/benefits-of-a-multilingual-digital-banking-system`.

Alboukadel Kassambara. Cox proportional-hazards model, 2020. URL `https://www.sthda.com/english/wiki/cox-proportional-hazards-model`. Accessed 23 October 2025.

Radheshyam Kollipara. Bank customer churn dataset. Kaggle dataset, 2022. URL `https://www.kaggle.com/datasets/radheshyamkollipara/bank-customer-churn`. Accessed 23 October 2025.

Saravana Kumar. Customer retention versus customer acquisition. *Forbes*, 2022. URL `https://www.forbes.com/councils/forbesbusinesscouncil/2022/12/12/customer-retention-versus-customer-acquisition/`. Accessed 23 October 2025.

Jim Marr. Stop chasing youth: Why aging americans are key to banking success, February 2024. URL `https://thefinancialbrand.com/news/demographics/stop-chasing-youth-why-aging-americans-are-key-to-banking-success-188117`.

Samir Meleis. Looking beyond products to customer lifetime value. *Novantas Review*, 2010. Average banking customer LTV $2,000–$4,000.

National Community Reinvestment Coalition. Age-friendly banking & low-to-moderate-income older adults, 2021. URL `https://ncrc.org/afb-standards/`.

Ke Peng, Yan Peng, and Wenguang Li. Research on customer churn prediction and model interpretability analysis. *PLOS ONE*, 2023. URL `https://pmc.ncbi.nlm.nih.gov/articles/PMC10707658/`. PMID: 38064499, PMCID: PMC10707658.

Pravin Pratap Singh, Fahim Ibne Anik, and Ranjan Senapati. Investigating customer churn in banking: A machine learning approach. *Data Science and Management*, 7(1):7–16, 2024. doi: 10.1016/j.dsm.2023.09.002.

Emily Smith. Plugging the leak: Retaining banking customers amid record switching, August 2025. URL `https://rfi.global/plugging-the-leak-retaining-banking-customers-amid-record-switching/`.