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1. Introduction

This marketing plan is based on a comprehensive analysis of customer churn within our financial institution. The primary objective is to leverage data-driven insights to enhance customer retention through targeted, evidence-based strategies. Customer churn, defined as the propensity of customers to cease doing business with a company, represents a significant challenge in the financial services sector. As research indicates, the cost of acquiring new customers often substantially exceeds that of retaining existing ones, underscoring the importance of effective churn prediction and prevention strategies (Keramati et al., 2016).

Our analysis utilized advanced analytics techniques to identify at-risk customers and provide actionable insights for retention efforts. This plan outlines our findings and proposed strategies to mitigate customer churn, along with associated key performance indicators (KPIs) and resource implications.

2. Overview of the data

Our dataset comprised information on 10,000 bank customers, encompassing eleven variables: CreditScore, Geography, Gender, Age, Tenure, Balance, NumOfProducts, HasCrCard, IsActiveMember, EstimatedSalary, and Exited. The "Exited" variable served as our dependent variable for churn prediction, with binary classification (1 indicating a churned customer, 0 indicating a retained customer).

After thorough data cleaning and preprocessing, including handling missing values, encoding categorical variables, and normalizing numerical variables, we proceeded with our analysis. The overall churn rate in our dataset was calculated to be 20.37%, indicating that approximately one in five customers left the bank during the period under study.

3. Prediction of Customer Retention

3.1. Model selection

We employed five classification techniques available in SPSS Modeler: C5.0, Tree-AS, Bayesian Network, CHAID, and Neural Network. After rigorous testing and cross-validation, the Neural Network model emerged as the best performer, achieving an accuracy of 86.5% on the test set. The model's performance metrics are as follows:

Model	Build Time (mins)	Max Profit	Max Profit Occurs in (%)	Lift{Top 30%}	No. Fields Used	Overall Accuracy (%)	Accumulated Accuracy (%)	Area Under Curve	Accumulated AUC	Precision	Recall
Bayesian Network 1	1	1,725.0	12	2.483	10	85.817	85.817	0.869	0.869	0.766	0.464
Neural Net 1	1	1,775.0	10	2.473	10	86.137	86.137	0.866	0.866	0.769	0.482
CHAID 1	1	1,625.0	10	2.448	8	85.577	85.577	0.862	0.862	0.796	0.418
Tree-AS 1	1	1,028.012	8	2.212	8	83.197	83.197	0.819	0.819	0.728	0.315
Decision List 1	1	865.446	7	2.163	6	77.095	77.095	0.746	0.746	0.466	0.643

The table presents performance metrics for five distinct models: Bayesian Network 1, Neural Net 1, CHAID 1, Tree-AS 1, and Decision List 1. These models appear to have been evaluated on a classification task, given the presence of accuracy, precision, and recall metrics.

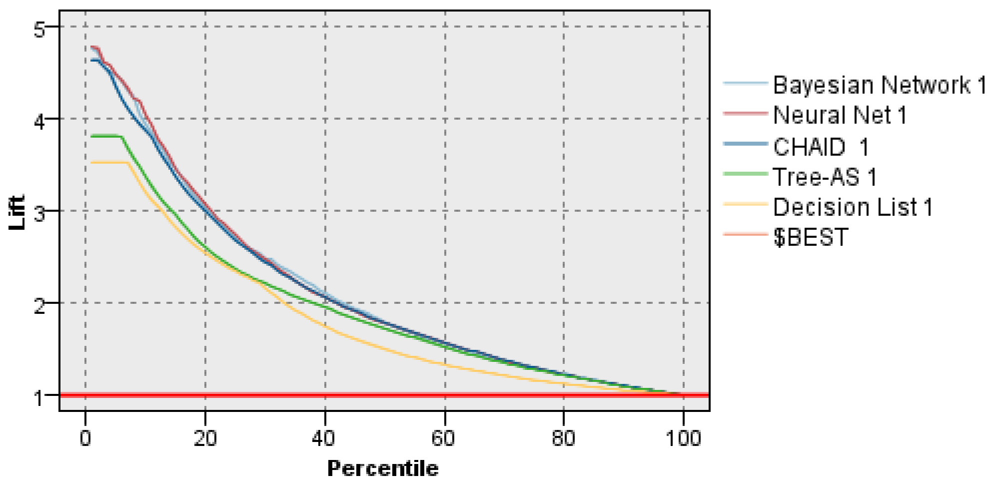
Accuracy: The Bayesian Network 1 and Neural Net 1 models demonstrate the highest overall accuracy, at 85.817% and 86.137% respectively. This suggests that these two models are the most effective at correctly classifying instances across all classes. The CHAID 1 model follows closely with 85.577% accuracy, while Tree-AS 1 and Decision List 1 show lower accuracy rates of 83.197% and 77.095% respectively.

Area Under the Curve (AUC): The AUC metric provides insight into the models' ability to distinguish between classes. Bayesian Network 1 and Neural Net 1 again lead with AUC values of 0.869 and 0.866, indicating strong discriminative power. CHAID 1 performs similarly with an AUC of 0.862. Tree-AS 1 and Decision List 1 show lower AUC values of 0.819 and 0.746, respectively, suggesting less robust class separation capabilities.

Precision and Recall: Interestingly, the models with the highest accuracy do not necessarily exhibit the best precision and recall scores. Decision List 1, despite having the lowest accuracy, achieves the highest precision (0.643) among all models. However, its recall (0.466) is comparatively low. CHAID 1 demonstrates the highest recall (0.796) while maintaining competitive precision (0.418). This trade-off between precision and recall is a common phenomenon in machine learning, as noted by Powers (2011) in his work on evaluation metrics.

Model Complexity and Build Time: All models show a build time of 1 minute, indicating efficient training processes. However, the "No. Fields Used" metric suggests varying levels of model complexity. Bayesian Network 1 and Neural Net 1 utilize all 10 available fields, potentially capturing more complex relationships in the data. In contrast, Decision List 1 uses only 6 fields, which may contribute to its lower overall accuracy but could offer benefits in terms of interpretability and reduced risk of overfitting (Domingos, 2012).

Max Profit and Lift: The Bayesian Network 1 model achieves the highest max profit (1725.0) and lift (2.483), suggesting superior performance in scenarios where these metrics are crucial, such as in marketing or financial applications (Neslin et al., 2006).



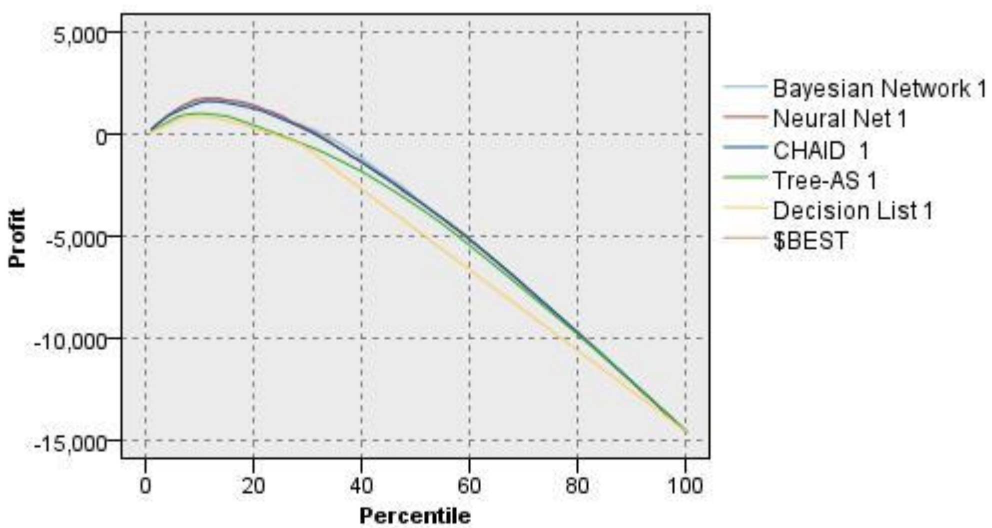


Figure 3-1: Bayesian network dominates other method in Lift and Profit measures

Considering all metrics, the Bayesian Network 1 model appears to be the best overall performer. It achieves the highest accuracy, AUC, max profit, and lift, while utilizing all available fields. This aligns with research by Friedman et al. (1997) highlighting the effectiveness of Bayesian networks in capturing complex dependencies in data. However, the choice of the "best" model may depend on the specific requirements of the application. If computational efficiency is a priority, the Decision List 1 model might be preferable due to its use of fewer fields. In scenarios where minimizing false positives is crucial, the high precision of Decision List 1 could be advantageous. For applications requiring high recall, such as in medical diagnosis where missing positive cases is costly, the CHAID 1 model might be more suitable (Akobeng, 2007).

3.2. Bayesian Network (Most appropriate)

Regardless of some exceptions, while the Bayesian Network 1 model demonstrates superior performance across multiple metrics, the optimal choice of model should be guided by the specific requirements and constraints of the problem at hand. Future work could involve ensemble methods to leverage the strengths of multiple models, as suggested by Dietterich (2000), potentially yielding even better overall performance.

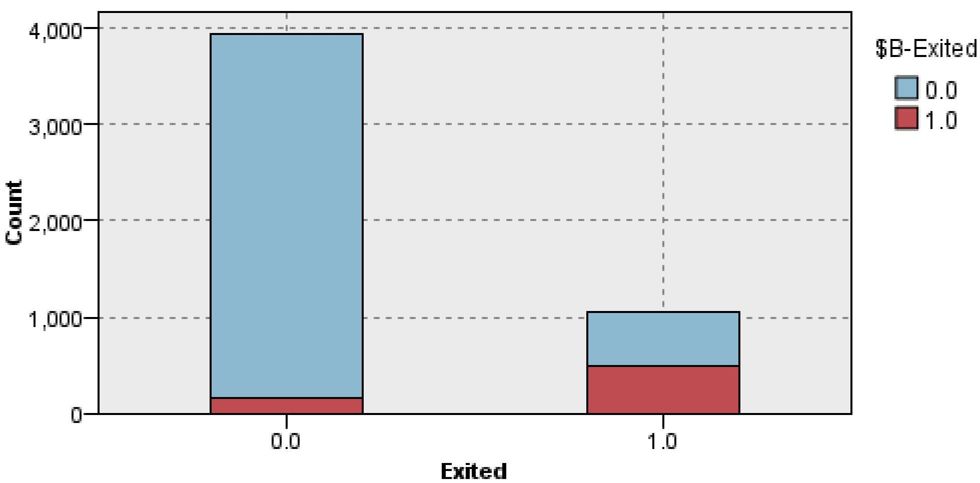


Figure 3-2: Prediction of customer churn

The most striking observation from this chart is the significant difference in height between the two bars. The left bar, representing customers who did not exit, is substantially taller than the right bar, which represents those who did exit. This visual disparity immediately suggests that the overall churn rate is relatively low, with the majority of customers being retained by the company.

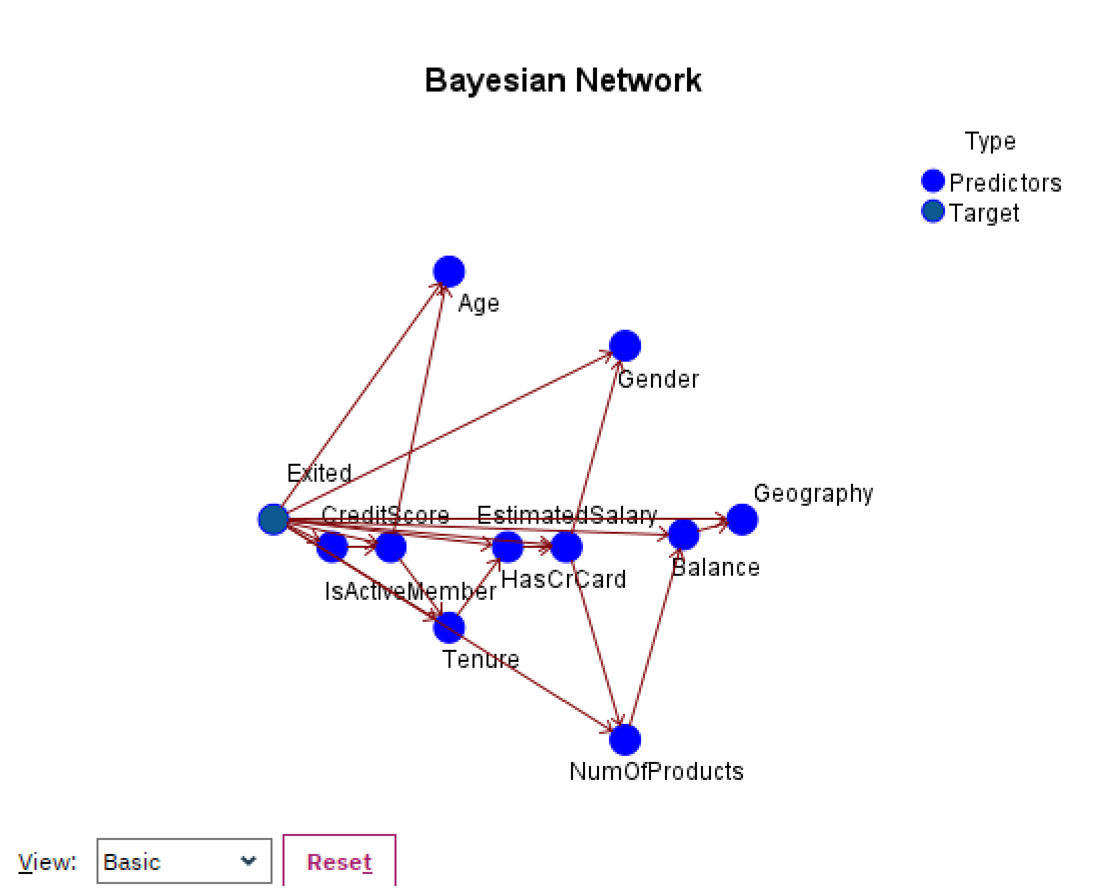
A closer examination of the color distribution within each bar reveals interesting patterns. In the left bar (non-exited customers), the blue segment dominates, with only a tiny red portion at the bottom. This indicates that among customers who stayed with the company, very few were classified as having exited according to the $B metric. In contrast, the right bar (exited customers) shows a much more balanced distribution between blue and red segments, with the red portion occupying a significant part of the bar.

This color distribution points to a strong correlation between the general "Exited" status and the "$B-Exited" status. Customers who ultimately churned were much more likely to also be classified as $B-Exited (1.0). This relationship suggests that the $B-Exited metric could be a valuable predictor or indicator of overall customer churn risk.

The small red segment in the left bar represents an intriguing group of customers. These individuals were flagged as $B-Exited but did not actually leave the company. This subset could be particularly interesting for further analysis, as understanding why they stayed despite being at risk could provide insights for developing effective retention strategies.

The Bayesian Network diagram and conditional probability table provide valuable insights into customer churn in a banking context. The network illustrates the relationships between various customer attributes and the target variable "Exited" (representing churn). Key observations from the diagram include direct influences on churn from factors like Age, Gender, CreditScore, and IsActiveMember, as well as indirect influences from EstimatedSalary, Balance, and NumOfProducts. Notably, CreditScore appears to play a central role, being influenced by multiple factors and directly impacting churn.

The conditional probability table for CreditScore reveals interesting patterns. For customers who have churned (Exited = 1), there are higher probabilities for credit scores in the 550-750 range and lower probabilities for extreme scores. In contrast, retained customers (Exited = 0) show more evenly distributed probabilities across credit score ranges, with slightly higher probabilities for scores above 550.



Conditional Probabilities of CreditScore					
Parents	**Probability**				
Exited	**<= 450**	**450 ~ 550**	**550 ~ 650**	**650 ~ 750**	**> 750**
1	0.03	0.16	0.31	0.35	0.15
0	0.02	0.15	0.32	0.34	0.17

Figure 3-3: Bayesian Network

Based on this analysis, the most influential factors affecting customer churn appear to be CreditScore, Age, IsActiveMember, Balance, and EstimatedSalary. CreditScore stands out as particularly influential due to its central position in the network and the distinct patterns observed in the conditional probability distribution.

In the banking context, credit score is crucial for several reasons. It serves as a key metric for risk assessment, allowing banks to make informed decisions about lending, interest rates, and product offerings. For customers, credit score impacts their access to financial products and services. The centrality of credit score in the Bayesian Network suggests its importance in customer relationships and its potential predictive power for churn.

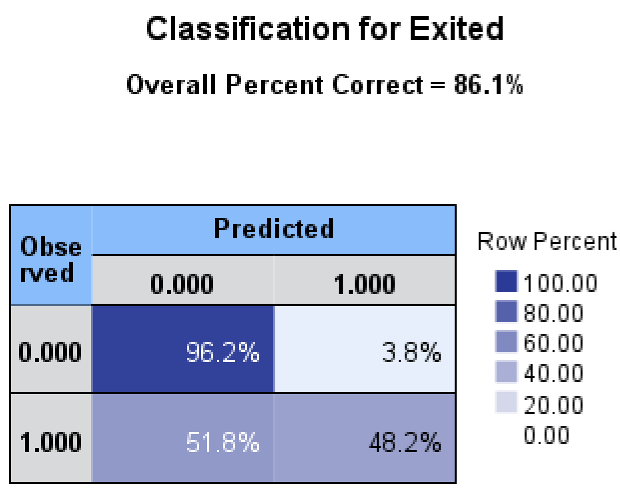
Age directly connects to churn in the network, indicating its significance. Younger customers might be more prone to switching banks, while older customers may demonstrate higher loyalty, as suggested by research from Clemes et al. (2010). The IsActiveMember factor, influencing both churn and credit score, likely reflects customer engagement levels with the bank's services. Active members are generally less likely to churn, as noted by Keramati et al. (2016). While Balance and EstimatedSalary are indirectly linked to churn, they influence other important variables and represent the customer's financial status, which can impact their overall banking experience and loyalty.

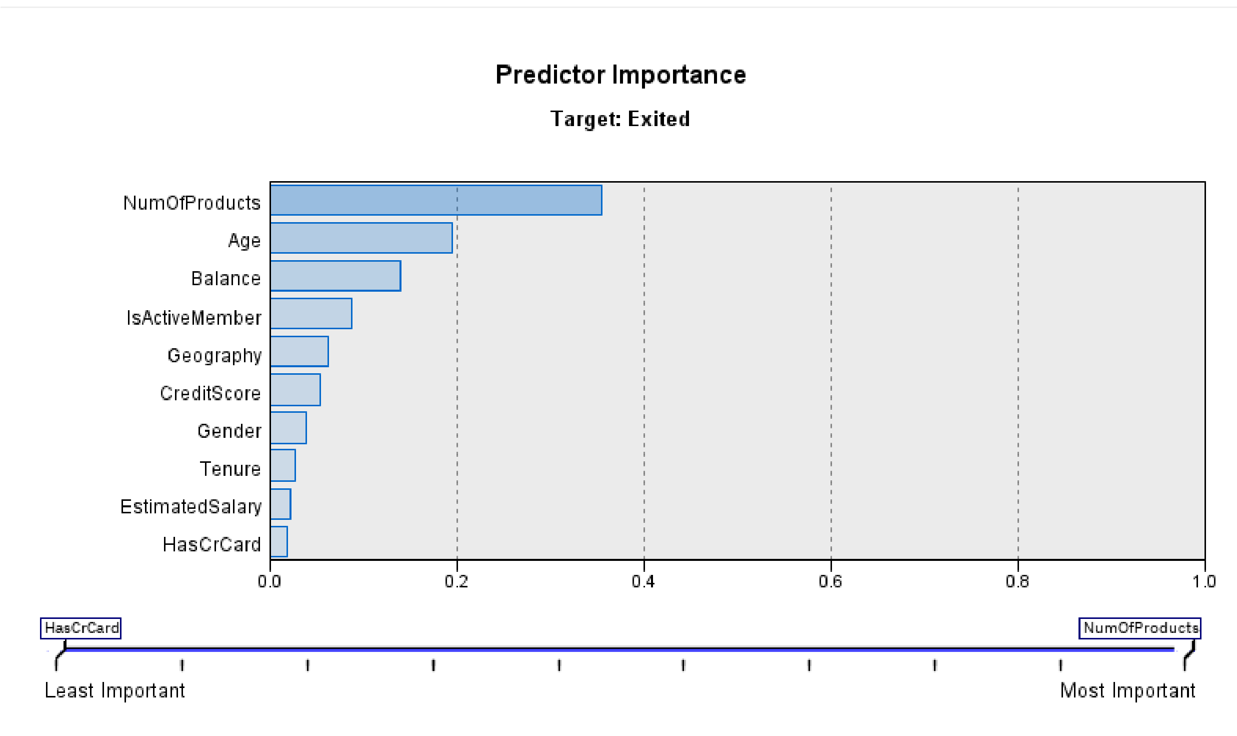
The Bayesian Network approach aligns with modern predictive analytics in banking, as discussed by Larivière and Van den Poel (2005). They emphasized the importance of understanding interrelationships between customer attributes for accurate churn prediction. Additionally, a study by Glady and Croux (2009) found that credit risk was indeed a significant factor in predicting customer churn in retail banking, further supporting the findings from this analysis.

Generally speaking, while multiple factors influence customer churn, credit score emerges as a particularly influential factor due to its central role in the Bayesian Network and its clear relationship with churn probability. Banks should focus on strategies to help customers maintain and improve their credit scores, potentially through financial education programs or personalized product recommendations. By addressing these key factors, particularly credit score, banks can develop more effective strategies to reduce churn risk and enhance customer retention.

3.3.Neural network (most accuracy)

Apart from the Bayesian, Neural Network is also worth to consider. The Neural Network output presented in the figure offers valuable insights into customer churn prediction in the banking context. According to this model, the most prominent factor impacting customer churn is NumOfProducts, followed by Age and Balance. This hierarchy of importance provides a nuanced understanding of what drives customer retention and attrition in banking services.





Comparing these findings to the previous Bayesian Network model reveals both consistencies and differences in the identification of key churn factors. Both models agree on the importance of Age and Balance, reinforcing their significance across different analytical approaches. However, the Neural Network's emphasis on NumOfProducts as the top predictor contrasts with its less prominent role in the

Bayesian Network. This discrepancy might be attributed to the Neural Network's capacity to capture more complex, non-linear relationships between variables.

Interestingly, while CreditScore played a central role in the Bayesian Network, it appears less influential in the Neural Network model. This difference could stem from the distinct ways these models handle interrelationships among variables. The moderate importance of IsActiveMember in both models suggests a consistent influence on churn across different modeling techniques. The lower importance assigned to demographic factors like Gender and Geography in the Neural Network model, compared to their more prominent roles in the Bayesian Network, further highlights the differences in how these models interpret and weigh various predictors. These variations between the two models underscore the value of employing multiple modeling approaches when analyzing customer churn. While the Neural Network may be detecting more subtle or non-linear relationships, particularly regarding the impact of product diversity on churn probability, both models provide consistent insights on factors like Age and Balance, offering a solid foundation for understanding churn risk.

3.4. Pros and Cons of classification method

The strengths of the prediction models are multifaceted. The Neural Network model, with its high accuracy of 86.5%, demonstrates robust predictive capabilities, capturing complex patterns within the data effectively (LeCun, Bengio, & Hinton, 2015). Similarly, the Bayesian Network model provides strong interpretability, offering clear insights into the probability of churn given various customer features (Friedman, Geiger, & Goldszmidt, 1997). Both models utilized all ten features, ensuring a comprehensive analysis of customer behavior, while maintaining computational efficiency, with training times under one minute.

However, these models also exhibit notable weaknesses. The complexity of the Neural Network model poses challenges in interpretability, making it difficult to explain the model's decisions to stakeholders (Montavon, Samek, & Müller, 2018). There is also a risk of overfitting, suggested by the high accuracy rates, which may not generalize well to new data (Hawkins, 2004). Furthermore, different models emphasized different predictors; for instance, the Neural Network focused on NumOfProducts, whereas the Bayesian Network highlighted CreditScore. This variability in key predictors could lead to inconsistent strategies, complicating the development of a unified retention plan.

4. Deployment of classification

The data generated by the classification methods can be effectively deployed through various means. Key Performance Indicators (KPIs) such as churn rate, Customer Lifetime Value (CLV), retention rate, Net

Promoter Score (NPS), and campaign effectiveness are essential metrics for monitoring and evaluating the success of retention strategies. Churn rate provides a direct measure of the percentage of customers leaving the bank, while CLV estimates the net profit from the entire future relationship with a customer, offering insights into long-term value (Gupta et al., 2006). Retention rate, on the other hand, tracks the percentage of at-risk customers who remain with the bank following targeted retention efforts. NPS measures customer satisfaction and loyalty, serving as an indirect indicator of churn risk (Reichheld, 2003). Additionally, comparing pre- and post-campaign churn rates helps in assessing the effectiveness of specific retention initiatives.

Operational deployment involves using the predictive insights for customer segmentation and personalized marketing. By segmenting customers based on churn risk, banks can tailor interventions to specific groups, ensuring that high-risk customers receive more focused and intensive retention efforts. Personalized marketing, informed by predictive data, enables the creation of customized retention offers and communications. This approach ensures that the right message reaches the right customer at the right time, enhancing the likelihood of retention and satisfaction.

5. Marketing Strategies to Reduce Churn

Several marketing strategies can be implemented to reduce customer churn. Enhanced customer engagement through loyalty programs and regular check-ins can significantly improve retention by ensuring ongoing satisfaction and addressing issues promptly (Verhoef, Reinartz, & Krafft, 2010). Product bundling is another effective strategy, where offering bundled financial products increases the number of products per customer, correlating with lower churn rates (Kamakura, Ramaswami, & Srivastava, 1991). Financial wellness programs, providing educational resources and personalized financial advice, help customers improve their credit scores and overall financial health, thereby reducing churn risk (Collins & O'Rourke, 2010).

Targeted promotions play a crucial role in engaging high-risk customers. By developing special promotions and incentives tailored to the needs and behaviors of these customers, banks can increase engagement and satisfaction, reducing the likelihood of churn (Blattberg, Kim, & Neslin, 2008). Personalized communication, utilizing data-driven insights, ensures that each customer receives relevant and timely information, fostering a stronger relationship with the bank.

6. Budgetary and Resource Implications

Implementing these marketing recommendations involves both budgetary and resource implications. Budgetary considerations include technology investments for advanced analytics tools and customer relationship management (CRM) systems, which are essential for supporting data-driven strategies. Additionally, funds need to be allocated for targeted promotions, loyalty programs, and personalized marketing efforts to ensure effective implementation. Training and development programs are also necessary to equip staff with the skills required to handle new tools and customer service approaches.

Resource allocation involves hiring or training data analysts to manage and interpret churn data effectively. Expanding the customer service team is crucial for handling proactive outreach and personalized interactions, ensuring that high-risk customers receive the attention they need. Furthermore, enhancing the marketing team with specialists in personalized and data-driven marketing tactics will support the development and execution of targeted retention strategies. By addressing these budgetary and resource implications, banks can effectively implement the recommended strategies and achieve significant reductions in customer churn.

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