Seneca POLYTECHNIC

BAN240 NAA: Business Analytics Consulting Capstone Project

Final Project Report

Leveraging Data Analytics to Reduce Customer Churn in Banking

Submitted by
Abdul Moiz Shaikh
Jacob Raj
Ankush Mehta
Shannon Delon Brohier
Pruthvish Patel
Vishwa Harshad

Submitted to
Professor Adenike Adesanmi

Submitted on
April 13, 2025

Table of Contents

Executive Summary

This report discusses how banks can leverage data analytics to understand and reduce customer churn, a key issue in the banking industry where it is more cost-effective to retain customers than acquire them. Since there is increased competition from fintech firms and digital banks, conventional banks have no option but to be data-driven to determine churn behavior and boost retention. Using the Kaggle "Bank Customer Churn Dataset," this project applies logistic regression to predict churn based on customer attributes and actions. The data consist of 10,000 observations with attributes such as age, credit score, tenure, product usage, and account activity. After data preprocessing and model training, logistic regression was used to identify the most significant predictors of churn.

Results show that older customers and customers with multiple products have higher chances of churning, with active members being much less likely to churn. The model was able to attain an accuracy level of 80.8%, presenting a sound and interpretable method for segmenting high-risk customers. The report advises targeted initiatives such as improved engagement via loyalty programs, the creation of easy-to-use tools for older customers, and streamlining products. These actions can help reduce churn and improve customer satisfaction. With a straightforward and powerful predictive model, banks can make educated decisions to optimize customer retention.

Introduction

In today's economic landscape, the banking industry has become highly competitive. With all the products and services in the market, retaining customers for long term success is harder than ever. From a customer's perspective, it is now easy to switch banks when the expectations about the level or value of the services are not met. This is known as customer churn, where customers stop using the banking services over a set period. It is one of the biggest challenges for banks today as acquiring new customers is more expensive and time consuming than retaining the existing ones (Invesp, 2023). Data analytics provides an opportunity for banks to better understand and analyze the factors that are dominant in the customers churned. This will be effective to develop effective strategies to reduce the customer churn rate. By analyzing customer behaviour and personal factors, banks can retain their existing customers through improved satisfaction and loyalty.

Customer churn has been a major challenge in the banking sector that has led to extensive revenue loss and increased costs. Many banks encounter problems in identifying the main reasons for customer churn, making it difficult for banks to implement targeted strategies. The usual marketing or retention strategies by banks target the broad population and fail to adequately address specific segments that are most likely to churn. Therefore, corporate resources are ineffectively utilized that costs the company in terms of customers lost.

The increased presence of digital bank and fintech companies has led to higher customer expectations (Forbes, 2024) about level of service and trust. During the first half of 2017, the Co-operative Bank lost 25,000 current account customers in a period of financial instability and restructuring. The bank's overall losses since its financial crisis totaled £2.6 billion, underscoring the dramatic effect of customer churn in periods of instability.

Consumers now place more value to personalised financial services and an enhanced customer service. Without a profound understanding about its customer segments and their churn behaviour, banks are at risk losing valuable customers consistently. This project aims to use business analytics to help banks understand this customer behaviour to identify churn predictors and develop strategies to reduce customer churn in the banking industry.

The report is organized into key sections that build a step-by-step understanding of customer churn and how data analytics can help reduce it. It begins by outlining the research objectives and key questions that guide the study. Next, the industry overview provides context on the Canadian banking sector and current trends. The literature review summarizes existing research on churn and highlights where this study adds value. The data description explains the dataset used and why it's relevant. The findings and analysis section presents the results from the logistic regression model, followed by a discussion of key insights. Based on these, the report offers practical recommendations for improving customer retention. It concludes with a summary of key takeaways and a discussion of the study's limitations and areas for future research.

Research Objectives

1. To identify major factors leading to customer churn in the banking industry.

2. To perform logistics regression for predictive analysis to identify churn patterns.

3. To recommend strategies for banks to improve their customer retention.

Research Questions

1. What are the factors associated with customers leaving their bank?

2. How can data analytics be used to predict customer churn?

3. What strategies can banks apply to increase customer retention?

Customer churn is a serious concern for banks that leads to financial and competitive losses. This project aims to leverage data analytics tools that can help banks identify the behaviors of customer churn and develop effective strategies to reduce customers leaving. By providing actionable insights in this report, banks can work towards improving their customer satisfaction and loyalty to ensure a sustainable profitability.

Financial Industry

Industry Overview

The Canadian financial sector covers a wide range of services, including banking, insurance, investments, and payment systems. It is a foundation of the economy, meeting the financial needs of individuals and businesses while driving growth and stability. Beyond traditional banking, the sector is advancing through technology like digitization and automation along with payment systems. It also plays a key role in ensuring compliance, protecting consumers, and managing risks.

Canada's banks are essential to the economy, contributing over $70 billion annually to GDP. They employ nearly 300,000 people, paying $30 billion in wages and benefits, and contributed $15 billion in taxes in 2023. That same year, they delivered $28 billion in dividends, helping households grow wealth. Banks also support small businesses, funding 61% of their financing needs, and spent $24.3 billion on goods and services in 2022. Their global reach is growing too, with 41% of income coming from outside Canada in 2020. Looking ahead, banks are focusing on AI, digital transformation, regulatory adaptation, and sustainability to meet changing demands.

The Canadian banking sector is influenced by a combination of factors that shape its growth and operations. The first of them being customer expectations, as customers increasingly demand convenient and personalized banking services, banks must innovate to meet these expectations. This explains another key driver- Technological advancements, innovations in the bank industry have led to the usage of AI and cloud computing in banking operations improving efficiency and reducing costs ("What Are Key Drivers"). This advancement in technology brings out competition, a key driver, as fintech startups as well as Big Tech companies like Facebook, PayPal and Apple challenge long-term domination held by banks, forcing them to innovate to stay ahead of the competition and retain customers (High).
The key players of the banking industry are Royal Bank of Canada (RBC), Toronto-Dominion Bank (TD Bank), Bank of Nova Scotia (Scotiabank), Bank of Montreal (BMO), and Canadian Imperial Bank of Commerce (CIBC). Along with the National Bank of Canada, they are often referred to as the 'Big Six'. The 'Big Six', at the end of 2022 held about 93 per cent of all banking assets in the country. It is the same share they held a decade earlier, and a decade before that (Bickis).

The banking industry has recognized the urgency of addressing climate change and understands that the financial sector is central to securing the transition to a low-carbon economy. This has resulted in multiple climate action plans, such as the 'Big Six' joining the Net-Zero Banking Alliance (NZBA), a global initiative focusing on achieving net-zero emissions, bank-led programs to limit the carbon footprint, issuance of green bonds to help finance new and existing green projects ("Banks in Canada").

Other than just environmental efforts, banks are progressively incorporating ESG (Environmental, Social, and Governance) principles into their core strategies that also include those related to customer engagement and retention. For example, several institutions are enhancing transparency in their lending practices, promoting financial inclusion, and prioritizing ethical customer treatment as part of their ESG commitments. These initiatives help in fostering long-term trust and loyalty among customers especially among socially conscious demographics, contributing to improved retention and brand value.

Literature Review

Over the last few years, reducing customer churn has become a top priority for most banks. Profitability, growth and sustainability are some of the important factors negatively impacted by customers frequently leaving their banks. The cost of acquiring new customers is significantly higher than retaining the existing ones (King, Chao, and Duenyas). Research by Lemmens and Gupta indicates that banks spend five times more on acquiring a new customer than on retaining a current one, proving that churn prevention is a significant business strategy (Lemmens and Gupta 956).

As a result, the banking sector spends considerable time and resources analyzing customer behavior and predicting customer churn. Early signs of customer churn, identified by Oyeniyi and Adeyemo, were to be reduced transactions, account status dormancy, and etc (Oyeniyi and Adeyemo 165).

Thus, to reduce customer churn, businesses analyze data to better understand customer behavior, identify the key factors that lead to churn, and uncover hidden patterns that are not immediately obvious by integrating data mining and machine learning tools.

A model derived from customer data permits banks to foresee potential churn and specifically target them with various corrective activities (such as promotions or gifts) to ensure their retention (Hassanien et al. 720). Zoric A. proposed a neural network-based model, analyzing data from a Croatian bank, and found that customers using more than three products are typically loyal, while younger users with fewer products, especially students, were more likely to churn (Zoric 116). Similarly, Dharwadkar and Patil evaluated the effectiveness of different machine learning models, including ANN, DNN, and SVM, on two datasets. Their study showed high accuracy for bank customer data—ANN (98%), DNN (97%), and SVM (92%)—but noted a drop in performance when applied to the German credit dataset. This contrast highlights the role of dataset context and quality in model performance. While Zoric emphasized customer segmentation by behavior and demographics, Dharwadkar and Patil focused on comparative algorithm performance. Together, these studies show that both model complexity and dataset characteristics significantly influence churn prediction, underscoring the importance of selecting the right tools for a specific banking environment. This synthesis also suggests that while advanced models may offer high accuracy, understanding the customer context is equally crucial for effective churn mitigation.

Another study focusing on customer churn in the banking sector compared multiple models, including artificial neural networks (ANN), random forest, decision trees, and logistic regression. Using a dataset of 10,000 customers with variables like age, gender, and credit score, the researcher applied Python encoders to convert categorical data and split the dataset into 80% training and 20% testing. The results indicated that ANN and random forest achieved the highest accuracy at 86%, followed by logistic regression at 81% and decision trees at 80% (Jagadeesan 444). In contrast, He et al. conducted a study on Chinese commercial banks using a much larger dataset of 50,000 customer records, applying both linear and RBF kernel SVM models for churn prediction. Their analysis showed that RBFSVM significantly outperformed linear SVM in recall and prediction rates, although both had similarly high precision scores (He et al. 423).

Comparatively, while Jagadeesan's study highlights the effectiveness of ensemble and deep learning models on relatively smaller and balanced datasets, He et al.'s work emphasizes the nuanced performance differences between kernel functions in SVM, especially on large-scale, time-segmented data. These studies collectively underscore that model performance can vary depending on dataset size, complexity, and preprocessing methods. The comparison also reinforces that while complex models often yield higher accuracy, the choice of algorithm must align with the data characteristics and business requirements to ensure practical applicability.

A study by Oyeniyi et al. focused on predicting churn rates in the banking sector using real customer data from a Nigerian bank, which included over one million records with 11 attributes. The data was processed in Weka and split into 66% for training and 34% for testing. K-means clustering was used to extract five clusters from the bank's database, yielding the best results compared to using two or three clusters (Oyeniyi and Adeyemo 192). This study analyzed a bank's database using data mining techniques, specifically classification. Three algorithms—J48 decision tree, MLP, and RF—were applied, with cross-validation and partition ratio techniques for comparison. J48 with cross-validation achieved the highest accuracy at 83.55%, outperforming MLP and RF. Precision measures like precision, recall, and F-measure also favored J48 (Alsubaie et al. 27).

Even after considering all the above customer churn reduction tools, the strategy is incomplete without evaluating the impact and efficient optimization of resources.

Implementing a data analytics solution is not a one-time initiative. It requires banks to consistently re-evaluate, refine and update their models to ensure that the predictive techniques are relevant to the different customer behaviors. Saha et al. emphasized that improving the quality and quantity of data can enhance data analysis, including churn prediction. Better consumer data leads to more accurate forecasts and higher profits. Additionally, incorporating data from both structured sources and unconventional ones, like social media feedback and support center complaints, can further strengthen the analysis (Saha et al. 4543).

Addressing Literature Gaps

The research will differ by using a simpler predictive model, like logistic regression, to analyse and predict customer churn, in contrast to advanced techniques like neural networks or SVMs used in existing studies. Logistic regression is particularly valuable for practical business applications because it provides clear, explainable results that non-technical stakeholders can understand and act on. Unlike complex models, which often operate as "black boxes," logistic regression allows for transparency in how each variable influences churn. This is crucial for decision-makers in banking institutions who need actionable insights, not just high accuracy scores. Using the Kaggle "Bank Customer Churn Dataset", this paper aims to show that basic models can still provide reliable predictions, offering an accessible and interpretable solution for banks with fewer resources. Key input features like credit score, age, balance, and tenure will be used to predict churn, with the target variable being 'churn' itself.

Data Description

The dataset (https://www.kaggle.com/datasets/gauravtopre/bank-customer-churn-dataset/data) for this study is sourced from Kaggle where it is open to use by the public for research papers and machine learning projects. It is a structured dataset in a CSV format with 10,000 rows and 12 columns. While the dataset initially appeared clean with no null or duplicate values, it still underwent essential preprocessing to ensure quality and model compatibility. Real-world datasets often contain inconsistencies or require refinement beyond simple null checks. In this study, categorical variables like “Gender” were label-encoded (Female = 0, Male = 1), and the “Geography” variable was one-hot encoded to convert country names into numerical format for the model. Additionally, all numerical features were standardized using the StandardScaler() function to bring them onto the same scale, avoiding bias during model training.

The data set includes customer information features, such as credit scores, age, tenure, number of products, and estimated salary along with a Boolean data type indicating if a customer has left the bank. Some of the features in the dataset are part of the Know your Customer (KYC) process by banks and there are no personal identifiers present in the dataset.

To ensure the integrity of this research and the results, the project has used data from only this one source. The study is committed to following ethical standards in data analysis and research. It strictly complies with Kaggle's Terms of Services and guidelines, ensuring that the usage purpose aligns with the platform's policies. However, the data being publicly available and anonymized, may not fully represent the diversity or complexity of real-world banking populations. Potential biases such as geographic imbalance or missing behavioral data should be acknowledged, as they can affect the generalizability of the findings.

This dataset is directly related to the study's objective of reducing customer churn in the banking industry. It contains key customer attributes such as demographics, financial details, and account activity, which is useful in our understanding of customer behaviour and our analysis of customer churn. Thus, the analysis can use data exploration methods such as logistics regression for predictive analysis.

Major Findings and Analysis, and Discussion

This section breaks down the key findings from the data analysis, explains what they mean, and discusses how they impact the banking industry when it comes to customer churn. The focus of this research is the predictive model built using logistic regression.

Data Findings

The "Bank Customer Churn Dataset" from Kaggle was used with 10,000 customer records across 12 columns, covering demographics, account details, and whether a customer churned. The dataset was loaded, and basic checks were run (df.head(), df.info(), df.shape, df.isnull().sum(), df.describe()) to understand the structure and ensure there were no missing values.

To perform logistics regression, the dataset was split into 80% training and 20% testing, ensuring the proportion of churned vs. non-churned customers remained the same (stratification). After this process, a logistic regression model was trained on the scaled training data as it is a great choice for understanding how different factors contribute to churn. This trained model was used to predict churn and then evaluated using a confusion matrix and key metrics like accuracy, precision, recall, and F1-score.

The logistic regression equation was built using the model's coefficients, showing how each factor influences the probability of churn. Following is the final equation.

P(Churn) = 1 / (1 + e^(-(-1.6459 + 0.0860 * credit_score - 0.2609 * gender + 0.7388 * age - 0.0201 * tenure + 0.0000 * balance + 0.4668 * products_number - 0.0860 * credit_card - 0.4907 * active_member + 0.0000 * estimated_salary + 0.4034 * country_Germany - 0.1857 * country_Spain)))

In this equation, P(Churn) represents the probability of a customer churning. The logistic function, 1 / (1 + e^(-z)), transforms the linear combination of variables into a probability between 0 and 1. The coefficients associated with each variable indicate the direction and magnitude of its influence on the likelihood of churn. For example, the positive coefficient for age (0.7388) suggests that older customers are more likely to churn, while the negative coefficient for active_member (-0.4907) indicates that active members are less likely to churn. Understanding these relationships allows the bank to identify key drivers of churn and develop targeted retention strategies.

The logistic regression model had an accuracy of 80.80%, meaning it correctly predicted most cases. To visualize the model performance, the confusion matrix (Figure 1.1) displays true positives, false positives, true negatives, and false negatives. It provides a clear representation of how well the model performed in identifying churned customers. The model predicted 1540 instances as "Retained" (0) correctly but misclassified 53 actual "Retained" instances as "Churned" (1). Conversely, the model correctly identified 76 "Churned" instances, while incorrectly classifying 331 actual "Churned" instances as "Retained." This indicates the model has a strong bias towards predicting "Retained," leading to low recall for the "Churned" class.

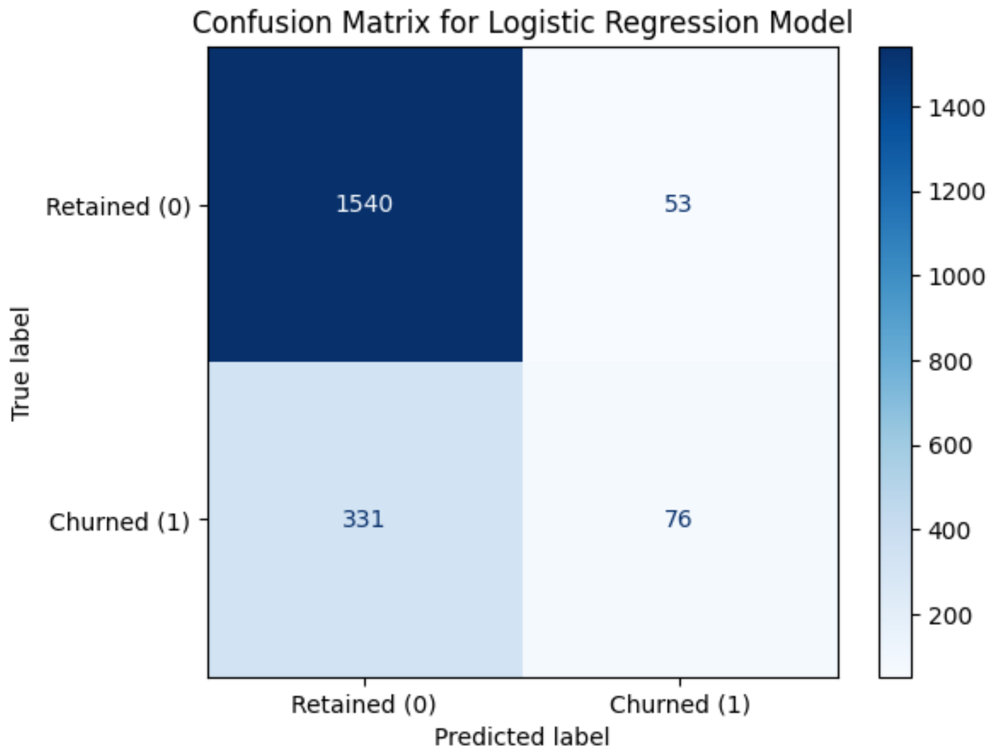

Figure 1.1

To add more depth to the analysis, three key visualizations were included. The churn distribution (Figure 1.2) shows a simple breakdown of how many customers churned versus how many stayed. This presents a good representation of the overall data which contains customers who have not churned. Secondly, the correlation matrix (Figure 1.3) checks for multicollinearity among independent variables, ensuring they do not interfere with each other’s impact on the model. As evident, the matrix confirms that multicollinearity is not an issue, meaning the model's coefficients are reliable and not interdependent on each other. Lastly, the feature importance graph (Figure 1.4) represents the predictive strength of variables with logistics regression. Findings indicate that age and active membership status play the most significant role in predicting churn among banking customers.

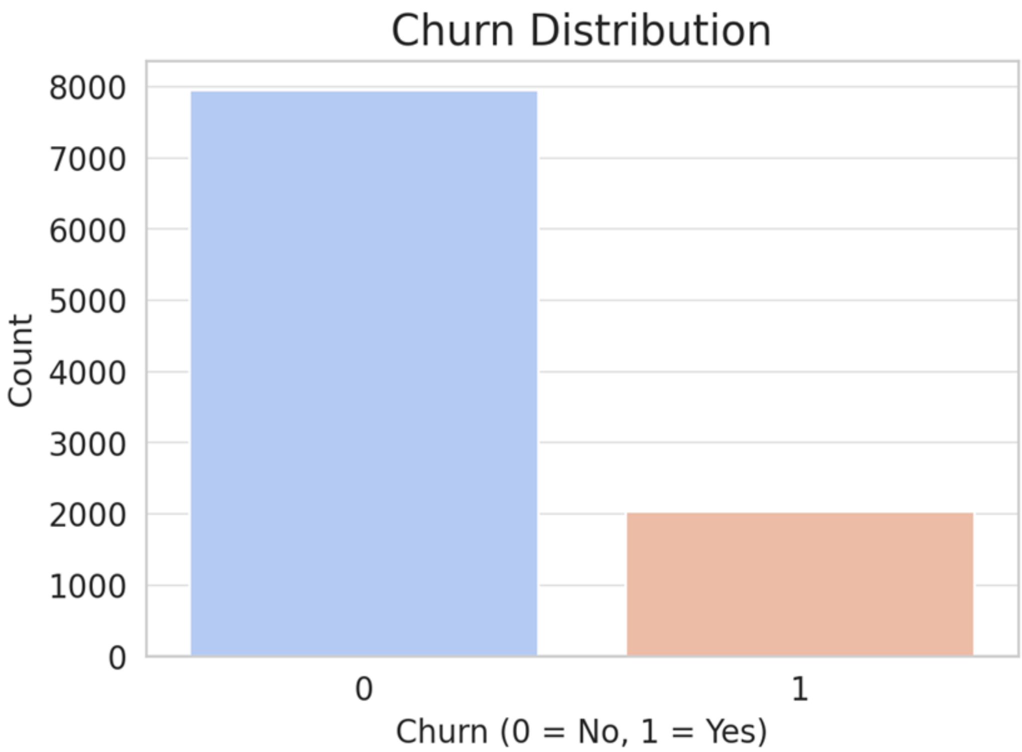

Figure 1.2

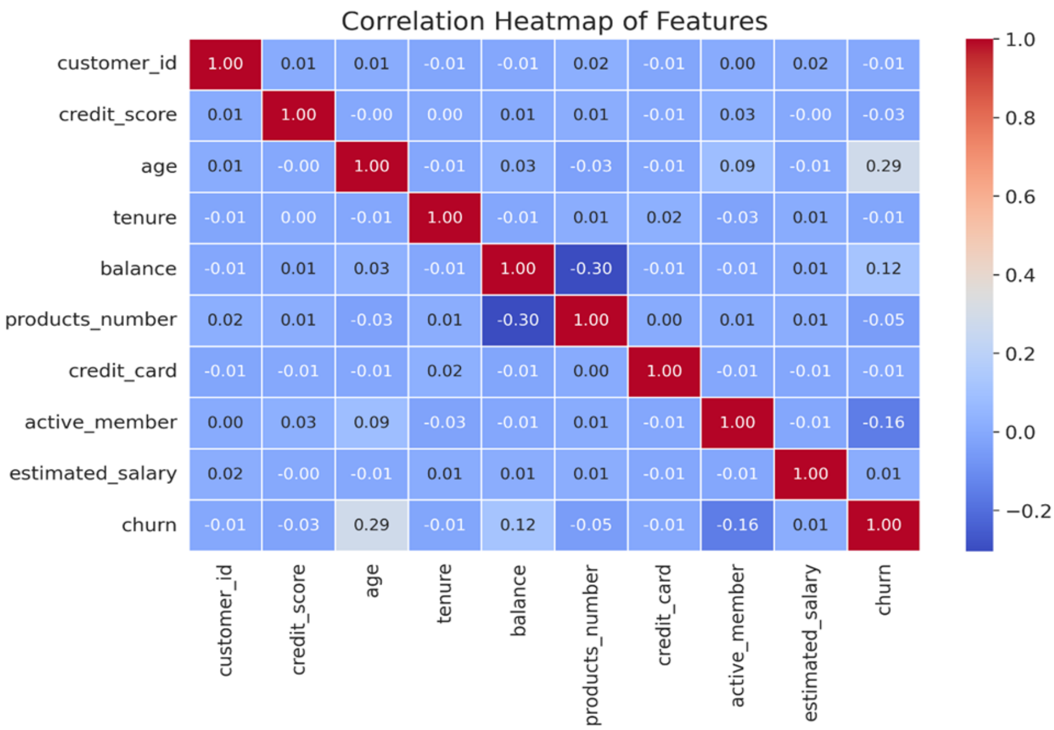

Figure 1.3

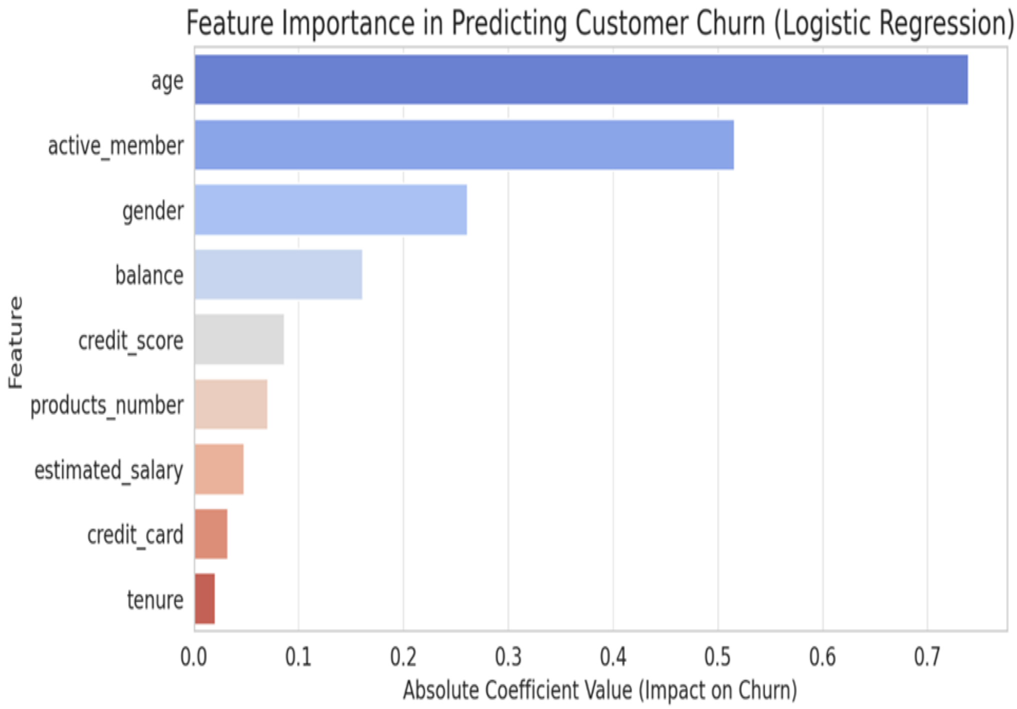
Feature Importance in Predicting Customer Churn (Logistic Regression)
Feature
age
active_member
gender
balance
credit_score
products_number
estimated_salary
credit_card
tenure
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Absolute Coefficient Value (Impact on Churn)

Figure 1.4

Analysis and Discussion: Major Factors Leading to Churn

Older customers were found to be more likely to leave the bank, primarily due to a lack of engagement with digital banking features and a limited number of services tailored to their specific needs. Many older clients may feel underserved when digital platforms do not accommodate their preferences or when they do not receive meaningful, personalized interactions. If banking services do not align with their expectations, they may seek alternatives that better meet their needs, such as traditional in-person banking services or competitor institutions offering more accessible solutions.

Additionally, the strong negative correlation between active membership and churn highlights the importance of continuous customer engagement. Customers who consistently interact with the bank—whether through personalized communications, special promotions, or loyalty rewards—tend to exhibit significantly lower attrition rates. This pattern suggests that frequent and meaningful engagement fosters a sense of connection and trust between customers and the bank, ultimately increasing their likelihood of staying. For instance, customers who receive regular updates about new products, exclusive offers, or financial planning assistance may feel more inclined to maintain their banking relationship.

Another key observation was that customers with a greater number of products had a higher churn rate. The data suggests that those who maintained only two products were more likely to stay with the bank, while customers holding more than two products showed an increased likelihood of leaving. Further analysis revealed that customers who retained their accounts tended to be younger, actively engaged, had higher-than-average credit scores, and were predominantly male. There are multiple possible explanations for this trend. One possibility is that customers with more products may struggle to manage multiple financial commitments effectively, leading to dissatisfaction and eventual attrition. Financial complexity, especially when combined with unclear terms, unexpected fees, or a lack of guidance from banking representatives, can create frustration and drive customers toward alternative banking solutions.

Lastly, customers with a higher number of products might have elevated expectations regarding service quality, support, and product benefits. If these expectations are not met, they may feel compelled to seek better options elsewhere. Managing multiple accounts, credit lines, or investment products requires a seamless and well-integrated banking experience. If customers perceive the bank’s services as inconvenient, inefficient, or lacking in support, they are more likely to move their business elsewhere.

Literature Support and Opposition

These findings align with existing research on customer churn in banking that logistic regression is widely used for churn prediction. While some studies favor more complex models (like neural networks or SVMs), this analysis shows that even a simpler model provides meaningful insights. Key churn drivers like demographics and account activity match prior research and studies highlight similar factors influencing customer retention. Additionally, model evaluation and refinement are critical. The literature emphasizes the need to continuously improve predictive models’ performance by incorporating more data sources and refining evaluation metrics. This study differs from others in its focus on simplicity. While many studies focus on complex algorithms, this analysis demonstrates that an interpretable model like logistic regression is still valuable—especially for banks with limited data science resources.

Recommendations: Strategies to Improve Banking Customer Retention

Several tactics can be used to increase client retention and deal with the main causes of churn. First, as older people are more likely to become disengaged, programs designed especially for them should be created. These may include tailored assistance, easy-to-use online resources, and focused advertising to cater to their need, which would raise satisfaction and lower attrition. It's also critical to encourage active customer participation. Customers are less likely to leave when regular encounters and better connections are fostered through loyalty programs, special offers, and tailored communications.

Effective churn mitigation also requires region-specific strategies. For example, examining feedback and conducting surveys to identify pain areas could help alleviate the higher attrition rates among German clients. In high-risk areas, modifying marketing and service strategies to accommodate local tastes and cultural factors might improve client loyalty and satisfaction. Additionally, reducing the complexity that frequently results in discontent among clients who manage several accounts or services can be achieved by streamlining the selection of goods and services provided. Overall satisfaction can be raised by integrating services and guaranteeing a flawless user experience.

Furthermore, banks could broaden data collection to include transactional histories and behavioral insights to improve retention efforts even more to maintain the "active membership" status that is negatively correlated to churn probability. This would provide them with a more complete picture of the requirements and preferences of their customers. Using sophisticated machine learning methods, like ensemble models or decision trees, they can also increase churn forecast accuracy without compromising interpretability. Finally, it is important to give priority to proactive churn mitigation techniques. Early intervention initiatives, such as outreach campaigns aimed at high-risk clients, can be directed by predictive insights. Maintaining the model's relevance and efficacy in client retention requires regular monitoring and modification to account for changing customer behaviors.

Conclusion

The analysis shows that logistic regression is an effective tool for understanding and predicting customer churn in banking. The model provides clear insights into key churn drivers, allowing banks to identify at-risk customers and develop targeted retention strategies. While precision and recall highlight some limitations, the overall findings reinforce the importance of data-driven decision-making and continuous model refinement. Moving forward, banks should consider expanding their data sources, improving feature engineering, and experimenting with more advanced predictive models to enhance churn analysis further.

Limitations of Study

The study provides valuable insights made towards understanding customer churn in the banking sector, however, some limitations should be highlighted. To begin with, basic logistic regression was used to model churn for the banks. The model provides interpretability and simplicity, but it may not capture complex relationships that advanced models such as neutral networks could capture. Due to this, finer details in patterns of behavior might go undetected. Secondly, there is a trade-off between accuracy and interpretability. Logistic regression leads to a clear understanding of variable effects; however, it forgoes some predictive power compared to black-box models. This trade-off may limit the model's ability in detecting less observable churn drivers or interactions between variables.

Another limitation is due to due to the data source as it is a publicly available dataset from Kaggle. Though it provides a structured and clean dataset suitable for analysis, but it may not reflect the full complexity or diversity of real-world banking data. The dataset lacks transactional behavior, customer feedback, and temporal changes that are often critical in understanding customer decisions.

Lastly, the dataset shows a static snapshot of customer information at a single point in time. This means it does not account for evolving customer behavior or longitudinal trends. These trends can be crucial for more dynamic churn prediction. Banks often benefit from tracking customer engagement over time and the lack of time-series data limits the depth of insight into churn progression.

Works Cited

Invesp. "Customer Acquisition vs. Retention Costs – Statistics and Trends." *Invesp*, 2023,
Forbes Technology Council. "The Rise of Digital Banking: A Paradigm Shift in Fintech." *Forbes*, 1 May 2024

Keefe, Blair W., and Eli Monas. "Canada's Financial Sector: An Industry in Transformation." *Torys*, 2020,

Canadian Bankers Association. *Canada's Banks: Delivering for Canadians*

PwC. *Next in Banking: Trends Transforming the Industry.* 2024,

"What Are Key Drivers for Innovation in Banking?" *InvestGlass*, 2024,

High, Matt. "Key Drivers Changing the Banking Ecosystem Landscape." *FinTech Magazine*, 2024,

Bickis, Ian. "How Big Banks Dominate Canada's Financial Landscape." *Global News*, 19 Apr. 2023,

"Banks in Canada Committed to a Net-Zero Economy by 2050." *Canadian Bankers Association*,

King, Gregory J., Xiuli Chao, and Izak Duenyas. "Dynamic Customer Acquisition and Retention Management." Journal of Marketing Research, vol. 58, no. 2, 2021, pp. 135-149. JSTOR,

Lemmens, A., and S. Gupta. "Managing Churn to Maximize Profits." *Marketing Science*, vol. 39, no. 5, 2020, pp. 956-973.

Oyeniyi, A. O., and A. B. Adeyemo. "Customer Churn Analysis in the Banking Sector Using Data Mining Techniques." *African Journal of Computing & ICT*, vol. 8, no. 3, 2015, pp. 165-174.

Hassanien, Salma Ahmed, et al. "Prediction of Customer Churn in the Banking Sector: Review." *Journal of Southwest Jiaotong University*, vol. 58, no. 4, Aug. 2023, pp. 720-xx. *ISSN: 0258-2724*

Dharwadkar, N. V., and P. S. Patil. "Customer Retention and Credit Risk Analysis Using ANN, SVM, and DNN." *International Journal of Society Systems Science*, vol. 10, no. 4, 2018, pp. 316-332.

Zoric, A. Bilal. "Predicting Customer Churn in Banking Industry Using Neural Networks." *Interdisciplinary Descriptions of Complex Systems*, vol. 14, no. 2, 2016, pp. 116-124.

Jagadeesan, A. P. "Bank Customer Retention Prediction and Customer Ranking Based on Deep Neural Networks." *International Journal of Scientific Development and Research*, vol. 5, no. 9, 2020, pp. 444-449.

He, B., Y. Shi, Q. Wan, and X. Zhao. "Prediction of Customer Attrition of Commercial Banks Based on SVM Model." *Procedia Computer Science*, vol. 31, 2014, pp. 423-430.

Alsubaie, Wafaa A., et al. "Predicting Customer Churn in Banking Based on Data Mining Techniques." *4th International Conference on Computational Intelligence in Data Science (ICCIDS)*, Mar. 2021, Chennai, India, pp. 27-39.

Saha, L., H. K. Tripathy, T. Gaber, H. El-Gohary, and E. S. M. El-Kenawy. "Deep Churn Prediction Method for Telecommunication Industry." *Sustainability*, vol. 15, no. 5, 2023, art. 4543.