Dean&Francis

ISSN 2959-6130

# From Prediction to Action: Integrating Counterfactual Analysis with Logistic Regression for Interpretable Customer Churn Intervention

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**Abstract:**

Customer churn critically impacts business sustainability, necessitating not only accurate prediction but also interpretable, actionable insights. This study addresses the gap between identifying churn drivers and formulating executable strategies. This paper employs logistic regression coefficient analysis on a bank churn dataset (n=10,000) to identify the top four churn drivers: active_member (coefficient: -1.042), country_Germany (0.733), age (0.732), and gender_Male (-0.488). Subsequently, virtual intervention experiments are designed to quantify the potential impact of strategic actions. For instance, a 10% increase in the proportion of active members is projected to reduce the churn rate by approximately 0.7%, from a baseline of 20.36%. Similarly, interventions on geographic composition, demographic structure, and gender ratio are also simulated, with their respective effects on churn rate meticulously quantified. The findings provide a rigorously quantified foundation for strategic decision-making. The intervention simulations enable prioritization of retention tactics based on their projected efficacy, allowing businesses to allocate resources optimally and implement the most cost-effective strategies to mitigate churn.

**Keywords:** Customer churn prediction; counterfactual analysis; logistic regression.

## 1. Introduction

Customer churn analysis plays an important role in helping businesses retain customers and optimize revenue. Machine learning models implemented in R have emerged as powerful tools for predicting churn and uncovering behavioral patterns. However, while current research predominantly focuses on predictive accuracy, complex models like deep learning, despite their strong performance, often fail to guide practical decision-making due to their "black-box" nature. In contrast, interpretable models such as logistic regression can identify key churn drivers through coefficient analysis, enabling targeted interventions.

In customer churn prediction, logistic regression is widely adopted for its interpretability [1-3]. For instance, Sun analyzed telecom data and found that each tier increases in local call duration raised churn risk by 25%, while frequent long-distance calls reduced it by 29%. The study also revealed that 78% of high-risk users were mid-tier customers, suggesting tailored local-call packages to improve retention [4]. In recent years, counterfactual analysis has emerged as a powerful method for causal inference, demonstrating significant value in fields such as policy evaluation. Wang et al. illustrate how methods like difference-in-differences can effectively assess the impact of policy interventions, such as the measurable improvement in air quality attributed to the Central Environmental Inspection policy [5]. The strength of this approach lies in its ability to construct counterfactual scenarios, isolating causal effects from confounding variables.

However, significant gaps remain in current studies. Most literature focuses excessively on improving model accuracy while neglecting the crucial step of translating interpretable results into concrete business actions. Although logistic regression can provide variable importance rankings, research on how to design executable interventions based on these findings. Furthermore, few studies incorporate cost-benefit analysis of intervention strategies, leaving businesses without proper guidance to evaluate the return on investment for different approaches. For instance, while research confirms that increasing customer service investment can reduce churn rates, the optimal resource allocation to maximize returns has not been thoroughly investigated.

This study explores the application of counterfactual analysis to customer churn prediction, aiming to bridge the critical gap between predictive analytics and actionable business strategies. Recognizing that enterprises require transparent, operational solutions beyond mere prediction results, this paper develops a comprehensive interpretability, intervention that transforms analytical insights into executable actions. Specifically, this paper employs logistic regression coefficient analysis to identify the top four churn drivers and quantify intervention impacts through statements. Methodologically, this paper innovates by integrating coefficient analysis with counterfactual prediction to design virtual intervention experiments. Using the bank_churn dataset as the empirical foundation, this study provides reproducible R code and practical business action templates, offering both academic rigor and immediate practical value for customer relationship management. This approach not only advances analytical methodology but also directly addresses the persistent disconnect between academic research and business implementation in churn management.

# 2. Method

## 2.1 Dataset Preparation

The dataset used in this study was sourced from the customer database of an international bank, comprising 10,000 anonymized records. Each data item includes 12 features, such as demographic information (e.g., country, gender, age), account characteristics (e.g., tenure, balance, number of products), and financial indicators (e.g., credit score, estimated salary). The target variable is binary churn status (1 = churned, 0 = retained) [6]. To ensure data quality, preprocessing steps were applied, including handling missing values, removing duplicates, and standardizing continuous variables. Categorical variables such as country and gender were one-hot encoded to facilitate model training. The dataset exhibits broad coverage across three European countries (France, Spain, Germany), with balanced distributions in age, gender, and account tenure, ensuring representativeness for analysis. During the data preprocessing stage, this paper first applied stratified sampling to split the dataset into training (80%) and test sets (20%), maintaining the original churn rate distribution. Subsequently, this study standardized all numerical variables and performed dummy variable conversion for categorical features to ensure compatibility with the logistic regression model.

## 2.2 Logistic Regression-based Modelling

Logistic regression is a classical statistical method for binary classification [7-9], valued for its interpretable probability outputs and widely applied in churn prediction and medical diagnosis [10]. In this study, it serves dual purposes: predicting churn risk and identifying key drivers to inform intervention strategies.

This study adopts a logistic regression model to analyze the driving factors of bank customer churn, demonstrating three distinct advantages over alternative methods. Primarily, the coefficients in logistic regression can be directly interpreted as the marginal effects of independent variables on churn probability, offering superior attribution clarity compared to black-box models (neural networks) - a critical requirement for business decision-making.

Methodologically, this research innovatively transforms model interpretability into actionable intervention strategies through counterfactual prediction: after identifying key determinants via coefficient analysis, this paper designs virtual experiments to project churn rate variations. This paradigm not only preserves the transparency inherent to traditional logistic regression but also expands the

ISSN 2959-6130

model's applicability through intervention simulations, effectively bridging statistical outputs with operational strategies. Particularly valuable in financial contexts requiring rapid strategy validation, this approach pioneers a practical framework for implementing interpretable models in real-world scenarios.

The model maps a linear combination of features to a probability between 0 and 1 via the sigmoid function. Unlike linear regression, it establishes a linear relationship between features and log-odds, with parameters estimated through maximum likelihood [10]. The formal equation is:

$$P(Y=1)=\frac{1}{1+e^{-(\beta 0+\sum_{i=1}^{n}\beta i+xi)}} \quad (1)$$

Here, P(Y=1) denotes the event probability, is the intercept, and quantifies the impact of feature $xi$ on log-odds. For instance, a negative coefficient implies reduced churn likelihood. All features exhibited VIF < 2, ensuring no multicollinearity concerns.

The workflow of this study adopts a closed-loop research design comprising three sequential phases: model training, subsequent feature selection, and concluding with intervention validation. Elastic-net logistic regression with 10-fold cross-validation identified key features (active_member, country, age, gender) whose standardized coefficients exceeded 0.1 with statistical significance (p<0.05). Counterfactual interventions then systematically manipulated: active_member (10%-30% inactive-to-active conversion), country (10%-30% Germany-to-France shift), gender (10%-30% male-to-female transition), and age (2-10 years reduction, floor=18). Each intervention maintained other variables constant with re-standardization, generating multidimensional effect matrices that quantify how churn probability responds to strategic adjustments. This granular approach enables data-driven decision-making for targeted retention campaigns.

## 3. Results and Discussion

From Table 1, it can be observed that the logistic regression analysis identified the top four drivers of customer churn based on coefficient magnitude: active_member1 (-1.042), countryGermany (0.733), age (0.732), and genderMale (-0.488). The negative coefficient for active_member1 indicates that active members are significantly less likely to churn, while the positive coefficients for countryGermany and age suggest these factors increase churn risk. For categorical variables, the coefficients are interpreted relative to their reference categories. The positive coefficient for countryGermany (0.733) implies that customers from Germany have significantly higher odds of churning compared to the baseline country (France), while countrySpain (0.015) shows a negligible effect, suggesting Spanish customers' churn behavior is statistically similar to the baseline. Similarly, the negative coefficient for genderMale (-0.487) indicates that male customers have lower log-odds of churning compared to the reference category (female), meaning males are less likely to churn when other factors are held constant. Notably, balance (0.166) and estimated_salary (0.030) had weaker effects, implying limited predictive power.

**Table 1. Coefficient Estimates of the Best Lambda Model**

| variable | Coefficient |
|---|---|
| (Intercept) | -0.99864938 |
| credit_score | -0.03365830 |
| countryGermany | 0.73257949 |
| countrySpain | 0.01491107 |
| genderMale | -0.48752338 |
| age | 0.73209544 |
| tenure | -0.04993710 |
| balance | 0.16566029 |
| products_number | -0.02790906 |
| credit_card | -0.03420954 |
| active_member | -1.04240967 |
| estimated_salary | 0.03020079 |

The weak influence of financial variables (credit_score: -0.034, estimated_salary: 0.030) suggests that customer churn is predominantly driven by non-economic factors. The substantial negative coefficient of active_member

(-1.042) highlights the critical role of customer engagement, where actively participating clients demonstrate significantly higher retention rates. This aligns with established theories emphasizing service experience over financial incentives in loyalty formation. The positive association between age and churn (0.732) may reflect differing service channel preferences across age groups, with older customers potentially less adapted to digital platforms. Geographic variations are evident in the stark contrast between Germany (0.733) and Spain (0.015), possibly indicating market-specific factors such as competitive intensity or cultural banking habits. The gender difference (-0.488 for Male) suggests potential behavioral disparities in financial service usage patterns that warrant further investigation. These findings collectively underscore that retention strategies should prioritize service quality and personalized engagement over monetary considerations.

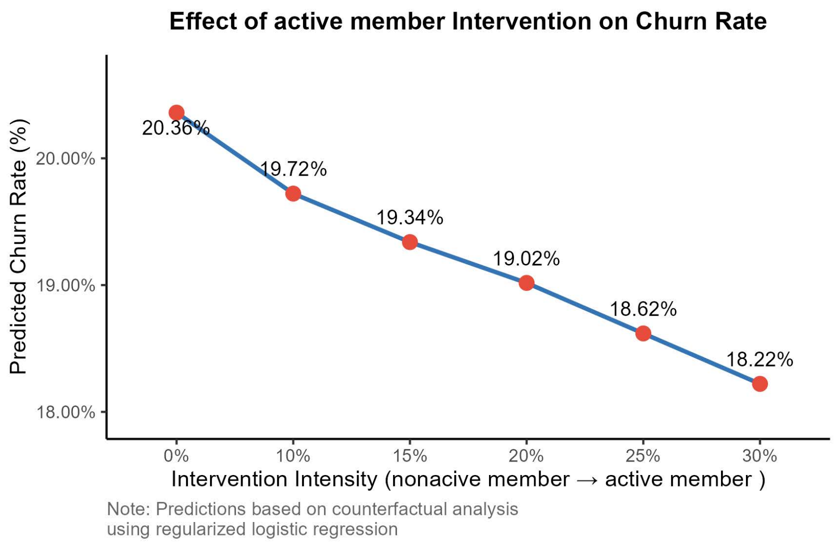


**Fig. 1 Effect of active member Intervention on Churn Rate (Picture credit : Original)**

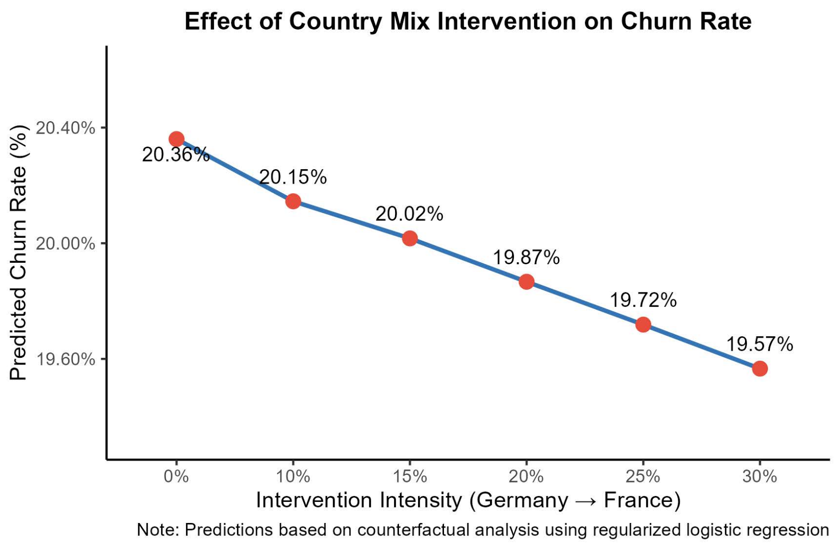


**Fig. 2 Effect of Country Mix Intervention on Churn Rate (Picture credit : Original)**

ISSN 2959-6130

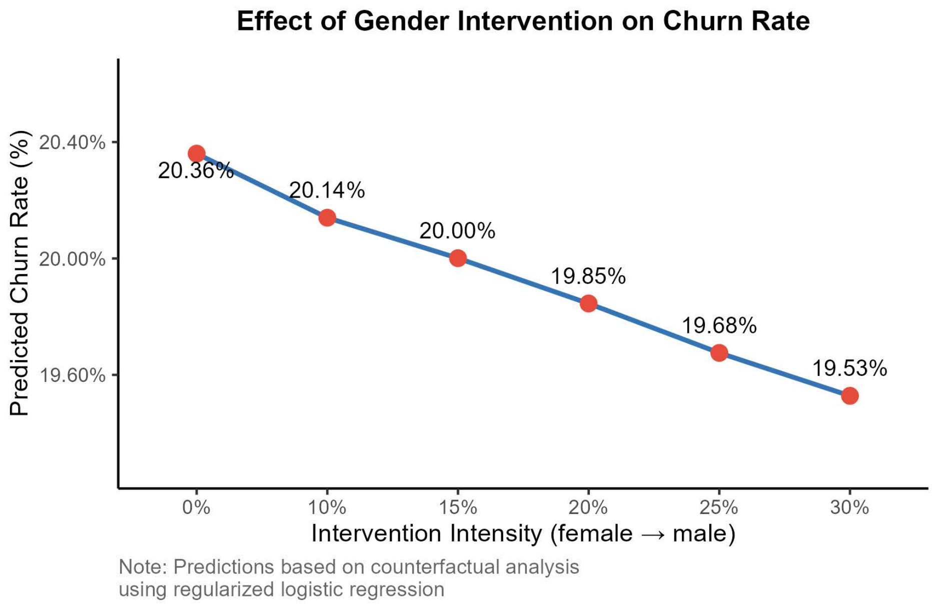


**Fig. 3 Effect of Gender Intervention on Churn Rate (Picture credit : Original)**

From Fig. 1, Fig. 2 and Fig. 3, the intervention experiments demonstrate varying effectiveness across different customer attributes. For active member status (coefficient: -1.042), increasing the proportion of active members from 0% to 30% yields the most substantial churn reduction, decreasing from 20.36% to 18.22%. The country mix intervention (Germany→France, coefficient: 0.732) shows a more gradual improvement, with churn declining from 20.36% to 19.57%. Gender modification (female→male, coefficient: -0.487) presents an intermediate effect, reducing churn from 20.36% to 19.53%. These results precisely mirror the relative magnitudes of their respective coefficients in the logistic regression model, confirming the predictive validity of the explanatory approach employed in this study.

The differential intervention outcomes reveal critical insights for strategic prioritization. The superior effectiveness of active member conversion, evidenced by its substantial coefficient (-1.042) and corresponding churn reduction from 20.36% to 18.22%, underscores engagement as the primary leverage point for retention. This likely stems from the cumulative effect of service utilization reinforcing customer loyalty through enhanced perceived value. The gender intervention's moderate impact suggests secondary potential in addressing behavioral differences, though this requires careful implementation considering ethical implications. Notably, the relatively limited returns from geographic intervention indicate that while country-specific factors influence churn, they represent less actionable targets for direct intervention. These findings collectively recommend a focused strategy beginning with customer activation programs, followed by demographic-sensitive service optimization, while treating geographic factors as contextual rather than primary intervention targets. The operational implementation should emphasize developing smart engagement triggers that automatically identify and reactivate disengaging customers, as this approach maximizes impact while maintaining scalability and ethical compliance.

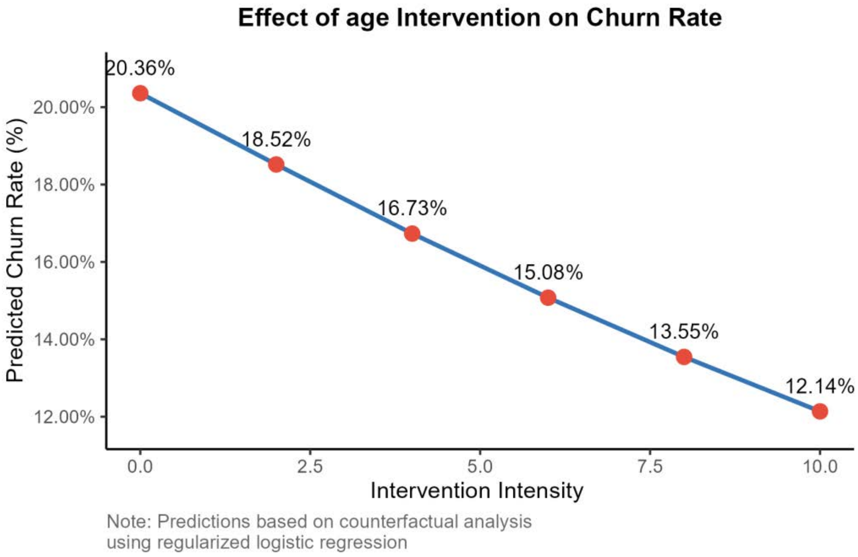


**Fig. 4 Effect of age Intervention on Churn Rate (Picture credit : Original)**

The age intervention analysis employed a distinct methodology from previous categorical variable tests, systematically reducing the average customer age by 2-year increments (up to 10 years total reduction while maintaining a minimum age of 18). As shown in Fig. 4, this continuous variable adjustment produced a near-linear churn rate reduction from 20.36% to 12.14 %. The intervention's mathematical construction differs fundamentally from the 10%-30% proportional conversions applied to binary variables like active member status, making direct comparison of absolute churn reduction percentages methodologically inappropriate. However, the consistent downward trajectory across all tested intervention intensities confirms age as a significant and reliably modifiable risk factor within model framework.

The exceptional responsiveness of churn rate to age reduction interventions warrants careful interpretation. While the positive age coefficient (0.732) initially suggests older customers are more prone to churning, the dramatic improvement from age reduction may reflect multiple underlying mechanisms: Digital platform adoption barriers among older demographics creating service friction, Life-stage financial needs changing with age (e.g., retirement transitions), or Cohort effects where different generations exhibit distinct banking behaviors. However, ethical and practical constraints make direct age-based targeting problematic. Instead, these findings suggest developing age-appropriate service adaptations - for instance, enhanced digital literacy programs for older customers or life-stage relevant product bundles. The results also highlight the need to examine whether observed age effects stem from true biological age or correlate with other age-related factors like technological adoption timing or wealth accumulation patterns.

## 4. Conclusion

In conclusion, this study bridges the critical gap between predictive analytics and actionable business strategies in customer churn management by integrating logistic regression with counterfactual analysis. This study not only identifies key churn drivers—active membership, country, age, and gender—but also quantifies the impact of targeted interventions through virtual experiments. The results demonstrate that enhancing customer engagement (e.g., increasing active members) yields the most significant churn reduction, while age-related interventions reveal nuanced ethical and practical challenges. Despite its contributions, this study is limited by its reliance on a single dataset and the inherent constraints of logistic regression in capturing non-linear relationships. Future research could explore hybrid models combining interpretability with advanced predictive power and validate findings across diverse industries.

## References

[1] Jain H, Khunteta A, Srivastava S. Churn prediction in telecommunication using logistic regression and logit boost. Procedia Comput Sci. 2020;167:101-112.

[2] De Caigny A, Coussement K, De Bock KW. A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision trees. Eur J Oper Res. 2018;269(2):760-772.

[3] Nie G, Rowe W, Zhang L, Tian Y, Shi Y. Credit card churn

ISSN 2959-6130

forecasting by logistic regression and decision tree. Expert Syst Appl. 2011;38(12):15273-15285.
[4] Sun L. Building a customer churn prediction model based on logistic regression algorithm. Inf Syst Eng. 2017;(06):134.
[5] Wang LJ, Yu WX, Huang Y. Counterfactual analysis + process tracing: An integrated approach to causal inference in social sciences. J Public Adm. 2024;17(04):177-194+200.
[6] Kaggle bank churn customer prediction dataset. Available from: https://www.kaggle.com/datasets/ameenhasan/bank-churn-customer-prediction-dataset
[7] Hosmer DW, Lemeshow S, Sturdivant RX. Applied logistic regression. 3rd ed. Hoboken: Wiley; 2013.
[8] Nick TG, Campbell KM. Logistic regression. In: Topics in biostatistics. 2007 Jan 1. p. 273-301.
[9] Stoltzfus JC. Logistic regression: a brief primer. Acad Emerg Med. 2011 Oct;18(10):1099-1104.
[10] Menard S. Applied logistic regression analysis. 2nd ed. Thousand Oaks: Sage; 2002.