Plagiarism Scan Report

3%
Plagiarism

0%
Exact Match

3%
Partial Match

97%
Unique

Words	560
Characters	4056
Sentences	40
Paragraphs	50
Read Time	3 minute(s)
Speak Time	4 minute(s)

Content Checked For Plagiarism

Findings Based on Observations

The data analysis revealed several customer characteristics and behaviours that were significantly associated with churn:

- Short Tenure: Customers with less than 3 months of usage were far more likely to churn, indicating early dissatisfaction.
- High Complaint Frequency: Users who contacted customer service multiple times were more likely to stop using the service.
- Low Service Scores: Customers rating the service poorly (low Service_Score and CC_Agent_Score) had higher churn rates.
- Payment Methods: Certain payment methods, such as UPI and Wallets, showed higher churn in contrast to users who used Credit/Debit cards.
- Device Type: Mobile-only users churned at a higher rate than multi-device users, possibly indicating lower engagement.

Findings Based on Analysis of Data

Using Random Forest modeling, the most important variables in predicting churn were:

- Tenure
- Service_Score
- CC_Contacted_LY
- Cashback
- Coupon_used_for_payment
- Account_user_count
- Payment method

The model achieved:

- Accuracy: ~82%
- Precision: ~76%
- Recall: ~68%
- AUC Score: ~0.85

These results indicate good discriminative power and acceptable performance, especially in identifying customers likely to churn.

General Findings

- Early-stage churn is a major issue, requiring onboarding experience improvements.
- Service and support-related features (like complaints and agent scores) are critical churn indicators.
- Incentives such as cashback and coupons help retain users, but effectiveness depends on targeting the right segments.
- Churn prediction is feasible with the available data and provides actionable insights for customer engagement strategies.

7.Conclusion and Recommendations

Recommendations Based on Findings

Based on the analysis and model outcomes, the following recommendations are proposed:

1. Improve Early User Experience

Customers with low tenure churn quickly. Enhance onboarding, offer welcome incentives, and provide personalized guidance during the first few months.

2. Enhance Customer Support Quality

High churn correlates with frequent customer service contact and low agent scores. Invest in better training, response automation, and post-interaction feedback loops.

3. Leverage Payment Method Insights

Offer incentives or loyalty points for using payment methods associated with lower churn (e.g., debit/credit cards). Educate users on secure and rewarding payment options.

4. Tailor Incentives Strategically

Coupons and cashback have a measurable effect on retention. Target high-risk users with well-timed offers to prevent churn, particularly after service issues or complaints.

5. Develop a Real-Time Churn Alert System

Integrate the predictive model into a CRM system that triggers alerts when high-risk customers are detected, enabling timely intervention.

Suggestions for Areas of Improvement

- Data Enrichment: Including behavioural data such as usage frequency, feature engagement, or app uninstalls could improve prediction accuracy.
- Customer Feedback Integration: Sentiment analysis of support tickets or reviews could enhance understanding of churn triggers.
- Churn Type Segmentation: Understanding voluntary vs. involuntary churn (e.g., payment failures) would allow more targeted strategies.

Scope for Future Research

- Time-Series Churn Prediction: Modeling churn as a time-to-event problem could better predict when churn is likely to happen.
- Customer Lifetime Value (CLV) Forecasting: Combining churn prediction with CLV estimation can optimize retention budget allocation.
- A/B Testing Retention Strategies: Test interventions driven by model insights (like offers or support outreach) to evaluate ROI.

Conclusion

This study successfully developed and validated a machine learning model to predict customer churn with strong accuracy and interpretability. Key churn drivers were identified, and actionable business strategies were recommended. With operational integration, this model has the potential to significantly reduce churn and improve customer lifetime value.

Matched Source

Similarity 3%

Title:Customer Loss during Onboarding - ABA Banking Journal

Aug 15, 2016 • The answer to slowing new customer churn is in creating a better onboarding experience. According to PWC, banking customer onboarding “starts•...Missing: stage requiring

https://bankingjournal.aba.com/2016/08/customer-loss-during-onboarding