PlaylistPro Retention Optimization
Executive Summary

To: Executive Leadership, PlaylistPro
From: Satkar Karki, Data Science Team, PlaylistPro
Date: November 10, 2025
Re: Customer Retention Optimization Analysis

Problem Statement

PlaylistPro faces a major retention challenge because more than half of its 125,000 subscribers have churned. This project applied descriptive, predictive, and prescriptive analytics to understand why customers leave, who is most at risk, and how to invest limited resources to achieve the highest retention return. The study connects data exploration with business action to help PlaylistPro strengthen engagement and profitability.

Methods

We employed a three-stage analytics framework. Descriptive analysis examined customer behavior patterns to identify churn drivers. Predictive analysis used four supervised learning models (logistic regression, stepwise logistic regression, random forest, and XGBoost) evaluated by AUC and F1-score to rank churn risk. Prescriptive analysis optimized retention actions using Mixed-Integer Linear Programming (MILP) in Gurobi under budget and capacity constraints with fairness protections across subscription tiers.

Key Findings

Descriptive Analysis: The descriptive analysis showed that churn affects the platform broadly rather than being limited to one customer group. Churn rates remained consistent across geography and payment methods, which indicates that customer behavior, not demographics, drives attrition. Our analysis identified key behavioral risk indicators: listening hours less than 10 per week, high song skip rates, and frequent subscription pauses. Customers who stayed active listened longer and interacted regularly with the platform. These behavioral findings guided the predictors we used in the next stage.

Predictive Analysis: We quantified individual churn risk using four supervised learning models. XGBoost achieved the best results with an AUC of 0.94 and an F1-score of 0.85 while avoiding overfitting. The model identified subscription type, customer service inquiries, listening hours, and skip rate as the strongest churn drivers. These insights gave PlaylistPro the ability to rank users by risk and focus on the behaviors most related to disengagement.
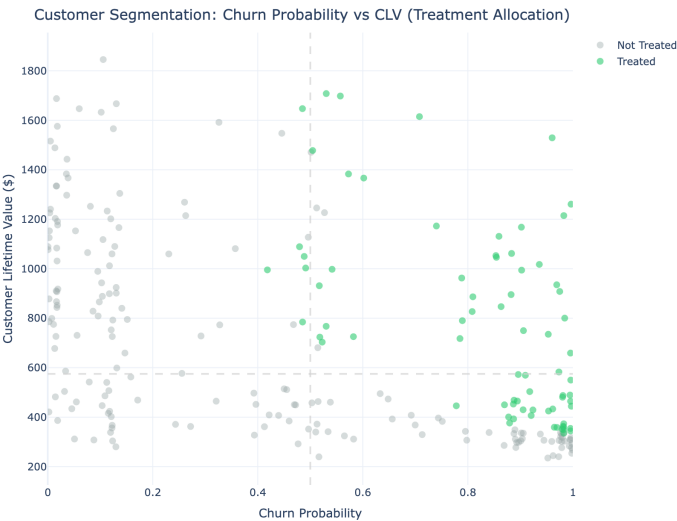

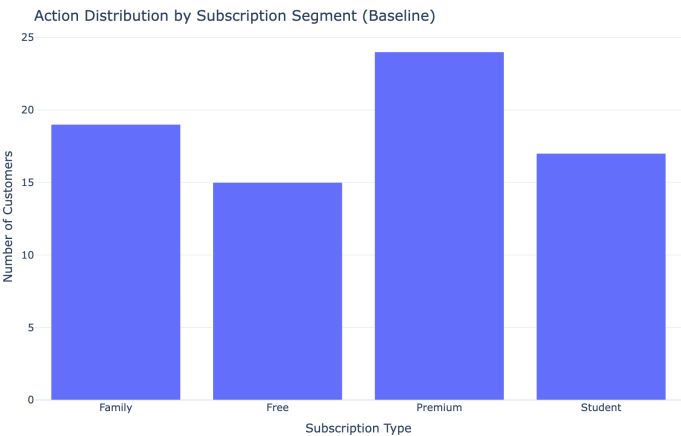Figure 1: Churn Risk vs. Customer Lifetime Value

Figure 2: Customer Segment Action Mix

Prescriptive Analysis: We translated these predictions into actionable decisions. Using a Mixed-Integer Linear Programming (MILP) model developed in Gurobi, the team optimized retention actions under

PlaylistPro's weekly budget and communication capacity. The optimization results demonstrate strong performance:

Performance Metric	Result
Weekly Budget	$150
Customers Targeted	75 of 250 (30%)
Net Retained Value	$3,478
Return on Investment	**2,319%**
Budget Utilization	100%

Sensitivity testing showed that although higher budgets increased total value, the benefits diminished after 400 to 500 dollars per week. This range defines the most efficient level of spending. Fairness constraints ensured that every subscription tier received equitable coverage, balancing financial goals with customer inclusivity.
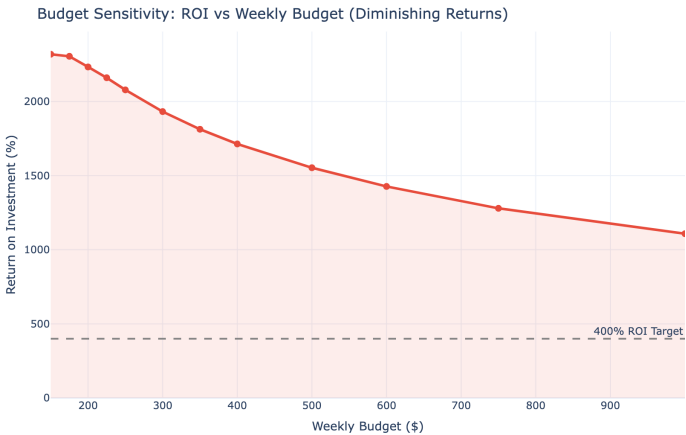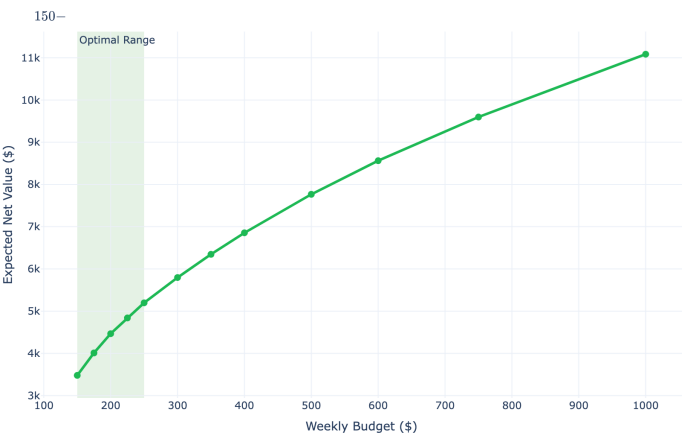

Figure 3: ROI vs. Weekly Budget

Figure 4: Net Value vs. Weekly Budget

Interpretation and Implications

Together, these analyses form an end-to-end data strategy. The descriptive stage revealed where churn occurs, the predictive stage measured risk and key drivers, and the prescriptive stage used optimization to recommend how to act. The framework allows PlaylistPro to prioritize high-value users, personalize outreach, and plan campaigns that maximize return on investment while keeping communication levels manageable. This integrated approach demonstrates that PlaylistPro can reduce churn and improve profitability by turning customer data into targeted, measurable, and fair retention decisions. PlaylistPro can now implement a data-driven retention strategy achieving over 2,000 percent ROI with optimal spending between 400 and 500 dollars per week.

Limitations

The current analysis focused on a sample of 250 customers rather than the complete 125,000 subscriber base, which may limit generalizability of budget recommendations. The model considers only one intervention type (personalized email offers) and assumes churn probabilities and customer lifetime values remain stable over the planning horizon. The model does not account for interaction effects between customers or long-term brand perception impacts. Future iterations should expand to additional intervention types, incorporate continuous model retraining, and scale to the full customer base.