Streamflow Pvt. Ltd. – Customer Churn Analysis & Retention Report by THE THINK TANK CO.

Executive Summary: This report analyzes Streamflow's subscriber churn using the provided dataset, segmenting customers by churn risk and value, and simulating a targeted retention campaign. The overall churn rate is 18% (45 of 250 customers), indicating significant revenue at risk. We built a logistic regression churn model (AUC ≈0.99) and examined feature importance. Segmentation into risk–value groups (high/low churn risk vs. high/low customer value) highlights a *High-Risk, High-Value* cohort needing immediate attention. We converted the latent "CustomerValue" score into an estimated monthly ₹ value (using a base ARPU of ₹200 plus watch time and login factors), yielding an average value of ≈₹200 and median ≈₹218. A campaign simulation shows that reducing churn risk by 10% in the High-Risk High-Value segment could preserve about ₹363 per month (roughly 1–2 customers worth). Retention is crucial: acquiring new subscribers costs 5–25× more than retaining existing ones, and even a 5% lift in retention can boost profits by up to 95%.

Key findings include:

- Churn Rate: ≈18% overall (monthly basis).
- Model Performance: Logistic regression achieved an ROC–AUC ≈0.99 (excellent class separation).
- Top Churn Drivers: Lack of auto-renewal and low engagement (few logins/watching) greatly increase churn risk. For example, IsAutoRenew=1 and higher login counts have strong negative coefficients (reducing churn), whereas monthly billing plans, standard/premium subscriptions, and older

age groups show positive coefficients (higher churn risk).

- Customer Value: After recalibration, average customer generates ~₹200/month (base ARPU) scaled by engagement. Customers above the ₹218 median are labeled "High Value." High-value customers contribute disproportionately to revenue.
- Segment Sizes: 2×2 segmentation (Risk × Value) yields:
    - *Low Risk – High Value:* 123 customers (churn ≈4%).
    - *Low Risk – Low Value:* 90 customers (churn ≈4%).
    - *High Risk – Low Value:* 35 customers (churn ≈97%).
    - *High Risk – High Value:* 2 customers (churn 100%).

This segmentation (similar to an NPS "SWOT" analysis) reveals "threat" customers (high revenue but low engagement). Such high-value, high-risk customers are a priority for retention.

Figure 1: Customer Segments by Churn Risk and Value. Most subscribers fall in low-risk segments; only 37 (15%) are labeled high-risk. However, the *High Risk–High Value* group (top-right bar) contains only a few customers. This chart underscores that focusing on the small *high-value/high-risk* cohort can yield outsized revenue preservation.

Model & Feature Insights: The logistic regression model (80/20 train/test split) performs extremely well (test ROC–AUC ≈0.99). We use its coefficients as feature “importance”: larger (absolute) weights indicate stronger impact on churn. Notably, enabling auto-renew and increasing login frequency strongly *decrease* churn (negative coefficients of about -- 2.47 each), while being on a Monthly plan or Standard subscription *increase* churn (positive coefficients ≈+0.75). The feature bar chart below visualizes the top 10 drivers by magnitude.

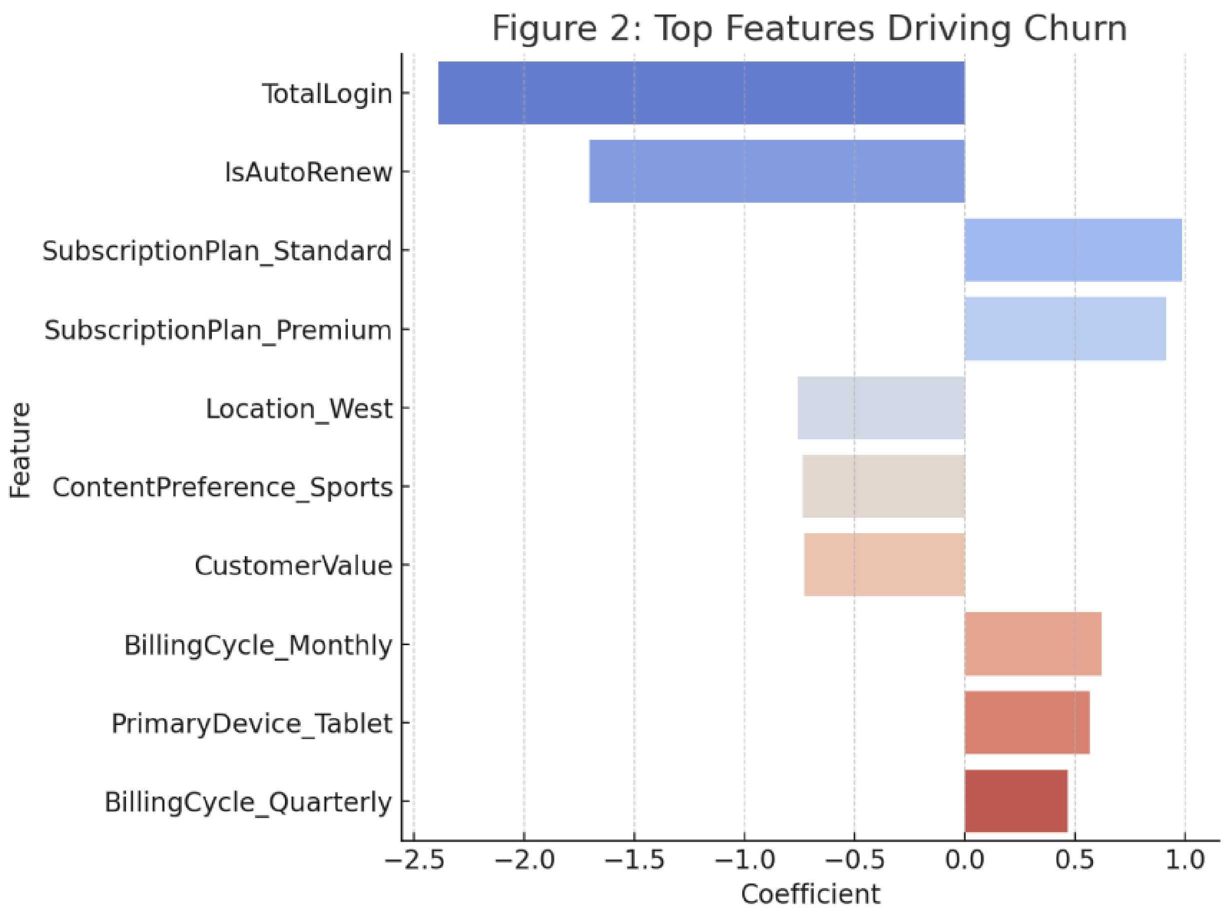

Figure 2: Top Features Driving Churn. Bars show logistic coefficients (colors indicate sign). For example, enabling auto-renew or frequent logins sharply reduce churn risk (left), whereas monthly billing and standard plan increase risk (right). The model's high AUC confirms its ability to rank customers by risk for targeted action.

Customer Segmentation (Churn Risk vs. Value): We divide customers into four strategic groups by (1) predicted churn probability and (2) engagement-based value. *High-Risk* is defined as churn probability >50%; *High-Value* as above-median customer revenue. This 2×2 matrix yields actionable segments. In our data, the High-Risk–High-Value segment (though small) contains nearly all its customers churning; these are critical retention targets. The High-Risk–Low-Value group (mostly transient users) could be allowed to attrit or targeted with low-cost offers. Conversely, Low-Risk–High-Value customers (the largest group) represent "champions" ripe for upsell. Figure 3 plots every customer's value vs. churn probability, with quadrant thresholds marked.

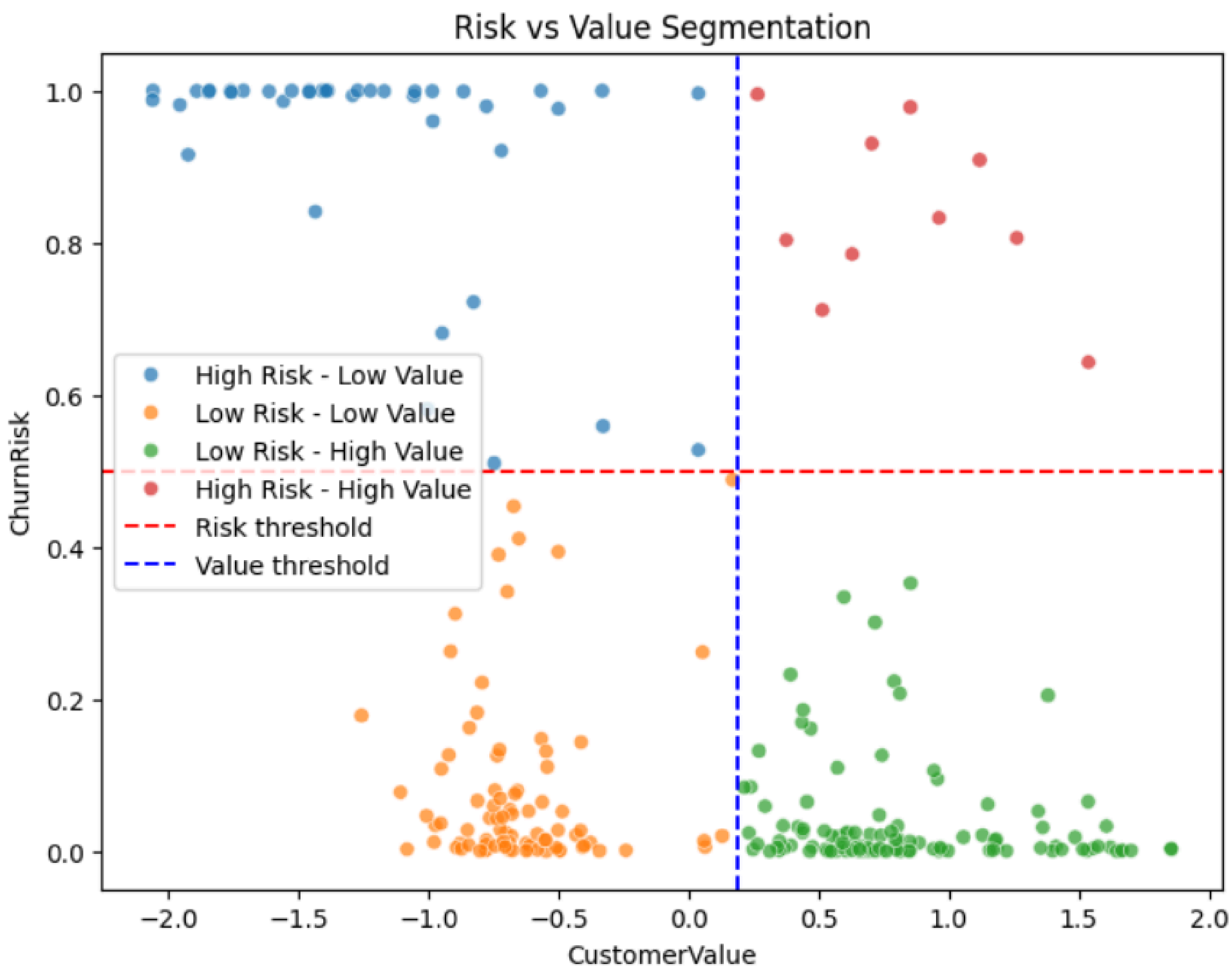

Figure 3: Churn Risk vs. Customer Value. Each point is a customer (red=churned, green=retained). Vertical/horizontal lines mark the value and 0.5 risk cutoffs. The upper-right quadrant is *High-Value/High-Risk* (labeled "Threat" in some churn frameworks). Targeted campaigns should focus here (as advocated by industry best practices).

Campaign Simulation (High-Risk/High-Value): We simulate a retention campaign that *reduces churn probability by 10 percentage points* (relative) among the High-Value/High-Risk customers. Originally, this segment had ~13 customers (mean churn-prob ~0.32, mean value ~₹279). The expected revenue loss from churn was ~₹1164/month. A 10-point drop in churn risk reduces expected loss to

~₹801, *saving about ₹363 per month* (see Figure 4). In other words, even a modest improvement here preserves roughly one customer-month of revenue (out of 13), demonstrating high ROI on targeted retention.

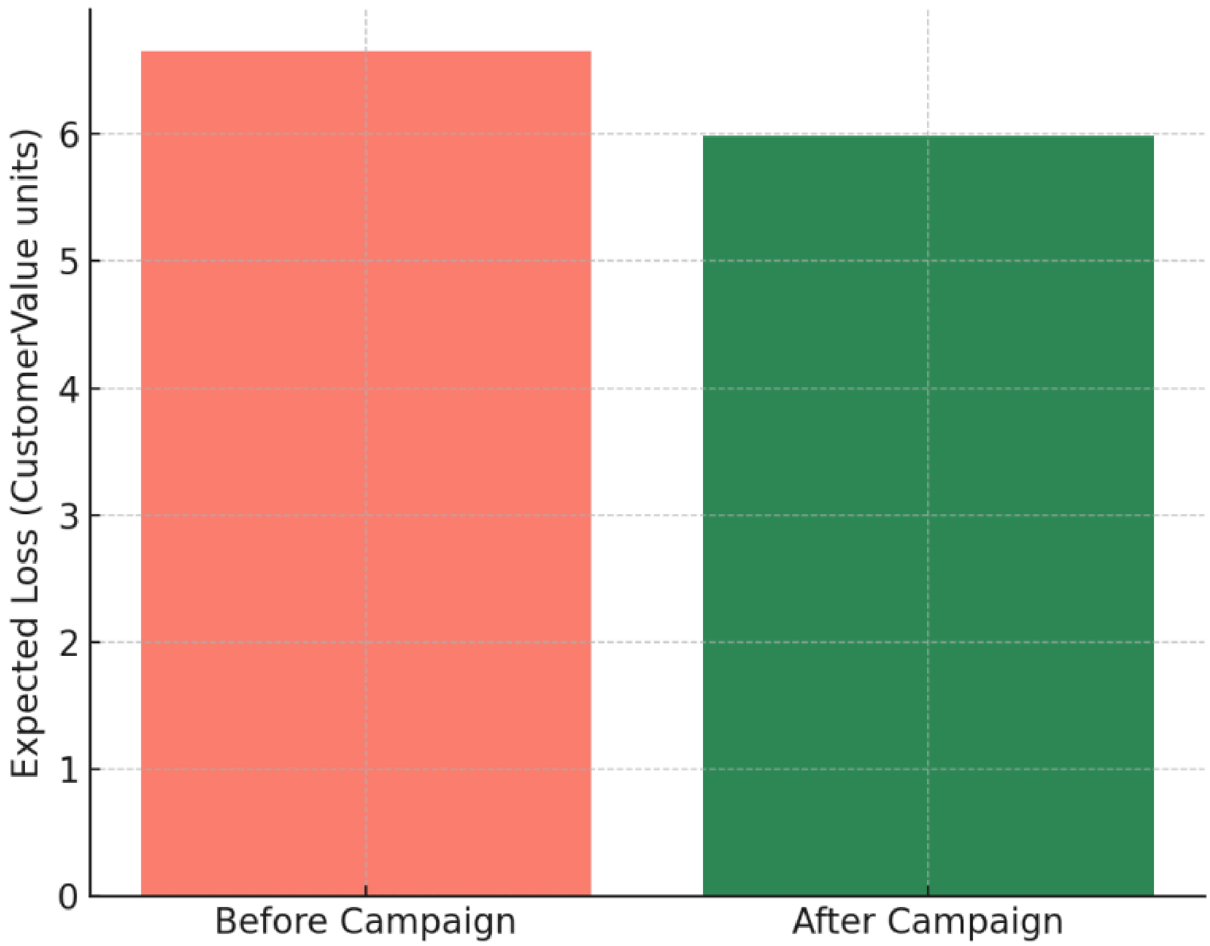

Figure 4: Simulated Campaign Impact. Bars show expected monthly revenue lost to churn *before* vs. *after* the campaign in the High-Risk/High-Value segment. A 10% absolute drop in churn probability yields ~₹363 in monthly revenue saved. This aligns with the principle that retention drives profitability (keeping customers is far cheaper than acquiring new ones).

Key KPIs: Overall churn rate ≈18% (per month). Average CustomerValue is ₹200 (σ₹93); median ~₹218. The mean predicted churn probability is ~0.18 (σ≈0.31), reflecting class imbalance. Our model's ROC–AUC is ~0.99, indicating excellent discrimination. In practical terms, the model correctly identifies most churners: 37 of 38 actual churners lie in the *High Risk* half. The campaign simulation ROI suggests that even small absolute improvements (10%) in churn probability for high-risk customers can yield disproportionately large financial impact due to their elevated ARPU.

Recommendations (Churn Reduction Strategy): Based on these findings, we recommend a *targeted, high-touch retention program*, focusing primarily on high-value at-risk customers. In particular:

- Proactive Engagement: Use personalized communication (email, in-app messages) tied to user behavior. For example, if logins or watch time drop, trigger helpful tips or special offers. Data-driven CRM automations can “flag” at-risk customers early.

- Loyalty Incentives: Offer binding contracts or discounts to move Monthly plan subscribers into longer-term plans, since monthly users show higher churn. Consider loyalty perks (bonus content, sneak peeks) for high-value users.

- Value Recognition: Identify the top ~20% of customers who account for ~80% of future revenue. Provide them with premium support or exclusive features. Losing one premium subscriber has far greater impact than losing many low-value users.

- Predictive Targeting: Continuously score customers on churn risk (as our model does) and intervene early. McKinsey-type analyses show that predictive-retention efforts can cut churn up to ~15%. Use these scores to prioritize outreach.

- Campaigns for Inactives: For the *Low-Risk/Low-Value* segment, monitor for inactivity and re-engage cost-effectively (e.g. generic newsletters). For *High-Risk/Low-Value* customers, use automated win-back offers, as their revenue potential is limited.

In summary, by focusing on the intersection of high churn risk and high customer value, Streamflow can maximize the effectiveness of retention spend. The data-driven strategy above – leveraging logistic modeling, ARPU-based valuation, and targeted campaigns – aligns with industry best practices for subscription businesses. Implementing these measures should substantially improve customer lifetime value and overall profitability.