

Turning Subscriber Churn into Retention Strategy

A Streaming Subscription Case Study

Agenda

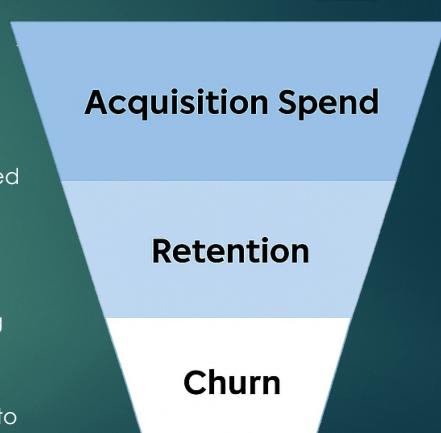
2

- ▶ Problem and Objective
- ▶ Data Overview
- ▶ Key Subscriber Insights
- ▶ Survival & Churn Drivers
- ▶ Modeling, Implications & Next Steps

Project Overview

Subscriber Churn Prediction Overview 4

- ▶ Today's streaming customers can cancel with ease – competition is only a click away
 - ▶ Reducing churn directly boosts lifetime value (LTV) and lowers costly acquisition needs
- ▶ Identifying at-risk subscribers early lets us deliver targeted offers that keep them engaged
 - ▶ Proactive retention strategies are essential – profitability depends on it
- ▶ Engagement and viewing trends provide early warning signals of potential churn
- ▶ **Key question:** Can we spot these signals early enough to act?



Objective

- ▶ **Step 1:** Define the Problem – Subscribers are leaving (churning) too soon
- ▶ **Step 2:** Explore solutions – Can we use data to understand which subscribers are likely to churn?
- ▶ **Step 3:** Evaluate Impact – What actions (e.g., offers, engagement, personalization, etc.) would improve retention while reducing costs?
- ▶ **Step 4:** Take Action – Build predictive models to identify at-risk subscribers and execute proactive retention strategies

What Data Do We Have to Predict Churn?

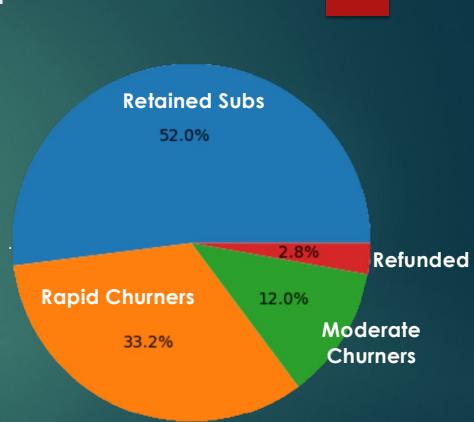
- ▶ **Sample Size:** ~29.7K subscriber records (January through mid-April 2023)
 - ▶ More history could reveal seasonal trends and strengthen predictive power
- ▶ **Demographics:** Limited or unavailable
 - ▶ Access to household and location data could improve churn profiling and predictive power
- ▶ **Subscriber Engagement:** Hours watched, distinct shows/channels, DVR saves, and stream starts
 - ▶ Can be key indicators of retention compared to churn
- ▶ **Payments and Lifecycle:** Payments, refunds, billing method/platform, acquisition method/platform
 - ▶ Can indicate loyalty and cancellation behavior

Insights & Findings

8

Subscriber Segmentation

- ▶ **Rapid Churners:** Subscribers who cancel after just 1 month
- ▶ **Retained Subscribers:** Subscribers who stay for 3+ months (into month 4 and beyond)
- ▶ **Other Groups (less focus):**
 - ▶ **Moderate Churners:** Subscribers who churned after 2 months
 - ▶ **Refunded/Trial Only:** Never converted after trial period
- ▶ **Note:** For the “insights” portion, the focus will be all groups except for the “Refunded/Trial Only” group. For the “predictive modeling” portion, the focus will only be “Rapid Churners” vs. “Retained Customers”

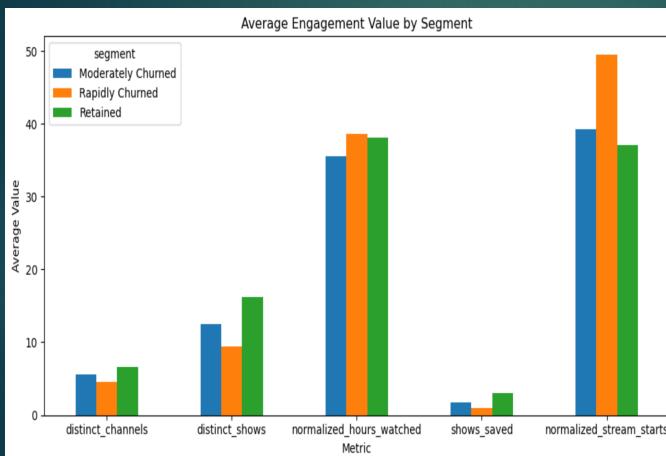


Engagement

10

Not All Engagement Equals Loyalty

High early usage may still lead to churn if it's just binge-watching behavior

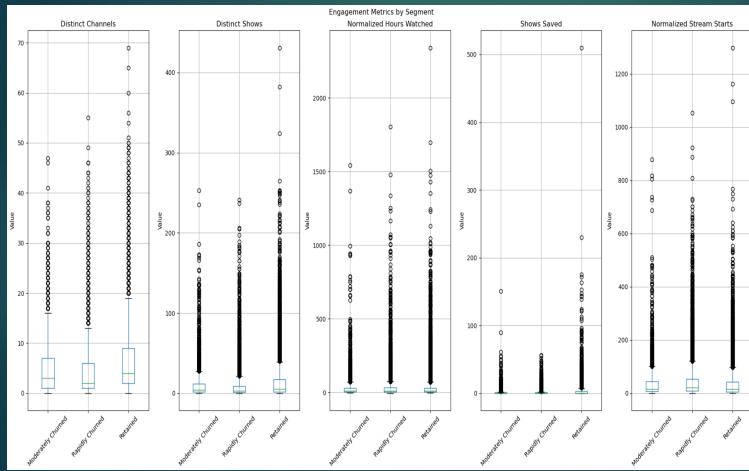


- **Rapid Churners Start Strong:** They show more stream starts and slightly higher hours watched (on average) in their first month compared to other groups
- **Possible Behavior:** They binge-watch favorite shows during their first month then cancel
- **Implications:** Retention risk isn't just about low engagement – some high engagement users churn once they've consumed what they came for
- **Takeaway:** First-month engagement patterns can reveal who may be testing the service short-term compared to those who are building lasting habits

*Note: Engagement metrics are normalized by active months to ensure fair comparison.

Engagement Distribution Insights

Wide spread of usage patterns shows that churn risk is linked to behavior



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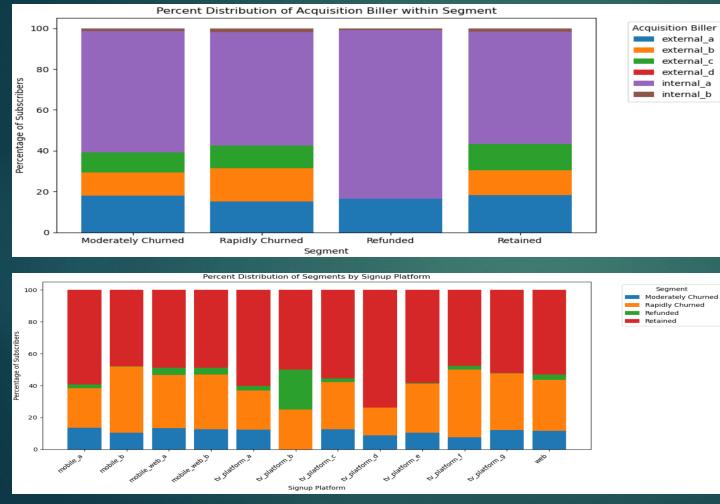
- **Stream Starts:** Rapid Churners show a wide spread and heavy skew, suggesting that these subs binge content intensely before canceling
- **Hours Watched:** Median activity for Raid Churners is similar to Retained Subscribers, reinforcing that high usage in month 1 does not guarantee long-term loyalty
- **Takeaway:** Churn risk can be tied to usage patterns and variability, not just total activity

Acquisition & Billing

Refunded Subscribers – Missed Opportunities

Refund patterns reveal friction in key acquisition channels

13

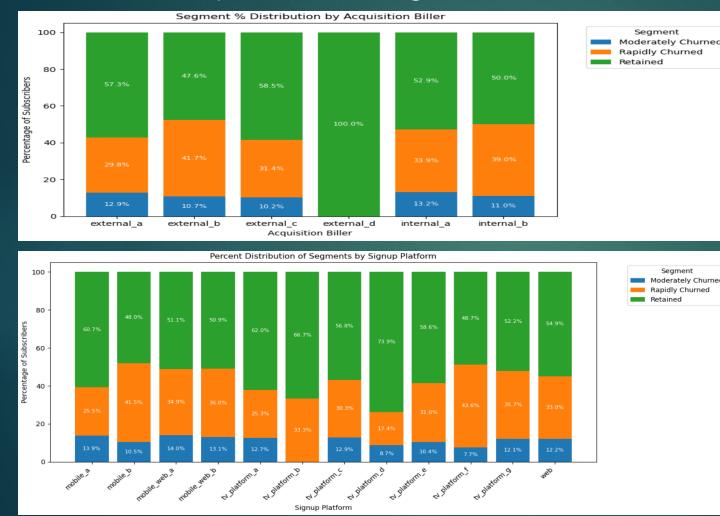


- Refunds don't have often (~2.8%, 830 subs) but highlight potential customer experience gaps
- Acquisition biller *Internal A* accounts for majority of refund requests
- TV Platform B shows noticeably higher refund rates than other signup platforms
- **Takeaway:** Small in volume, but refunds point to channel specific onboarding issues; Improving these could prevent early churn and lost trust

Churn Risk Varies by Acquisition Channel

Some billers and platforms drive higher churn than others

14



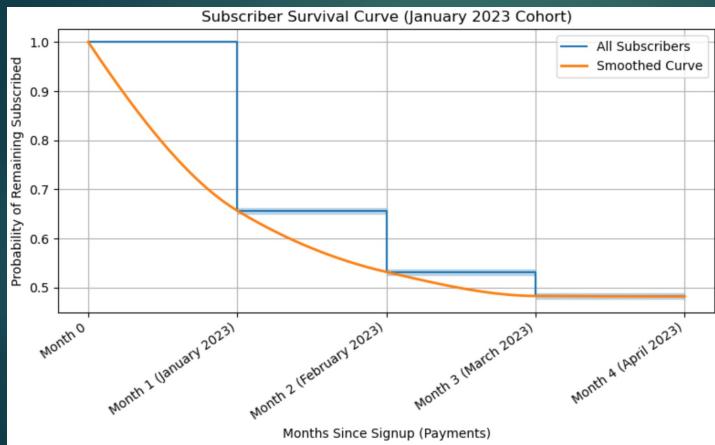
- **Acquisition Billers:** External B and Internal B churn ~9% higher than other billers
- **Signup Platforms:** Mobile B and TV Platform F have highest churn (>40%), compared to the ~34% average across platforms
- These patterns suggest certain acquisition paths attract shorter-tenure subscribers
- **Takeaway:** Targeting acquisition toward lower-churn billers and platforms or improving the onboarding experience in higher churn channels can directly improve retention and reduce wasted spend

Survival Analysis

16

Early Retention Defines Long-Term Survival

Most churn happens in the first month – retention stabilizes after month 2



Month	Survival Rates
January 2023	65.7%
February 2023	53.2%
March 2023	48.3%
April 2023*	48.2%

- The steepest drop-off occurs immediate after month 1, showing how critical the first month is
- After month 2, the decline flattens – subscribers who stay past this point are far more likely to remain
- This highlights the importance of strong onboarding and early engagement strategies to capture long-term value

*Note: April 2023 data incomplete

Summary – What Drives Churn

17

Not all engagement equals loyalty – early behavior pattern and acquisition channel drive churn

- ▶ **"Binge and Leave" Pattern:** Rapid churners show higher first-month stream starts and slightly higher hours – suggesting they binge what they came for and then cancel
- ▶ **Habit builders retain:** Longer-tenure subs show steadier, sustained usage patterns, aligning with higher retention
- ▶ **High-Churn Channels:** External B and Internal B billers; Mobile B and TV Platform F signups exhibit above-average churn
- ▶ **Refunds → Indications of Friction:** Refunds are small in volume but are concentrated in specific billers/platforms, pointing to possible onboarding issues
- ▶ **Survival Insight:** Most attrition occurs after month 1, then stabilizes after than
- ▶ **Takeaway:** Churn risk is concentrated in the first month – subscribers who binge in month 1 or signed up via higher churn channels are least likely to stick

Predictive Model

Predictive Model Results

The model gives some ability to flag early churners, but overall accuracy is limited due to data limitations

19

- ▶ **Overall Accuracy:** Modest predictive lift over baseline
 - ▶ ~2/3 precision when predicting churn
 - ▶ Useful for prioritization, not perfect prediction
- ▶ **Takeaway:** Even simple models can guide early retention focus when combined with channel and behavioral insights

Implications and Next Steps

More data is needed to make churn predictions actionable

20

- ▶ **What Works Today:** There are higher churn risks from certain acquisition billers and signup platforms
- ▶ **Current Limitations:** Without early usage data (such as weekly engagement to understand early engagement behavior), the model can't separate the "binge and leave" from the "habit builders"; It would be helpful to have more demographic data as well
- ▶ **Future Improvements:** Add early engagement data, expand timeframe beyond four months – such as more historical data, as well as include other cohorts who subscribe to understand if this is a recurring pattern or if this is unique to this cohort
- ▶ **Business Impact:** Even with modest accuracy, we have been able to identify higher-risk acquisition channels/platforms that can guide onboarding and retention focus now