

SaaS Churn Analysis

1. Business Context & Problem Statement

Business Context

The company operates a **subscription-based SaaS product** where revenue depends on **recurring payments and sustained customer engagement**.

While overall revenue trends appear stable, leadership has observed a **significant volume of canceled subscriptions**, raising concerns about long-term retention and revenue predictability.

Churn is costly not only because of lost revenue, but also because acquiring new customers is significantly more expensive than retaining existing ones.

Core Business Problem

Why are customers leaving the platform, and how can churn be reduced through targeted, data-driven actions?

Traditional churn reporting answers *who churned*, but fails to explain *why*.

This analysis reframes churn as a **behavioral problem**, enabling actionable insights rather than reactive reporting.

2. Analytical Framing: How the Problem Was Approached

Instead of treating churn as a single outcome, the problem was reframed around **customer behavior over time**.

What behavioral signals indicate that a customer is at risk of churn?

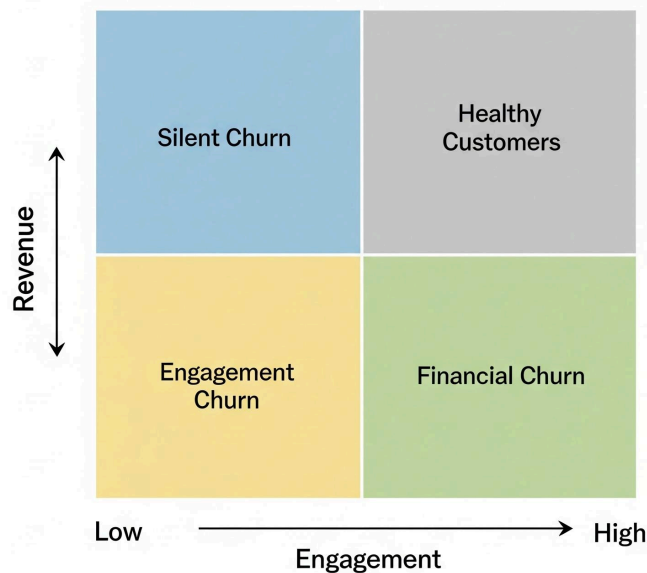
Core Framing Logic

Customers interact with the SaaS business through **two fundamental dimensions**:

1. **Revenue Behavior** – subscription payments and transactions
2. **Engagement Behavior** – logins, feature usage, and activity events

Churn can occur when **either dimension weakens**, or when both decline simultaneously.

Churn Framing: Revenue vs Engagement



3. Hypothesis Development (Initial Assumptions)

Based on SaaS industry patterns and stakeholder concerns, three hypotheses were formed:

Hypothesis 1: Financial Churn

Customers may churn by **stopping payments**, even if they previously used the product actively.

Potential drivers:

- Pricing dissatisfaction
- Budget constraints
- Loss of perceived value

Hypothesis 2: Engagement Churn

Customers may churn by **stopping product usage**, even if they have not formally canceled yet.

Potential drivers:

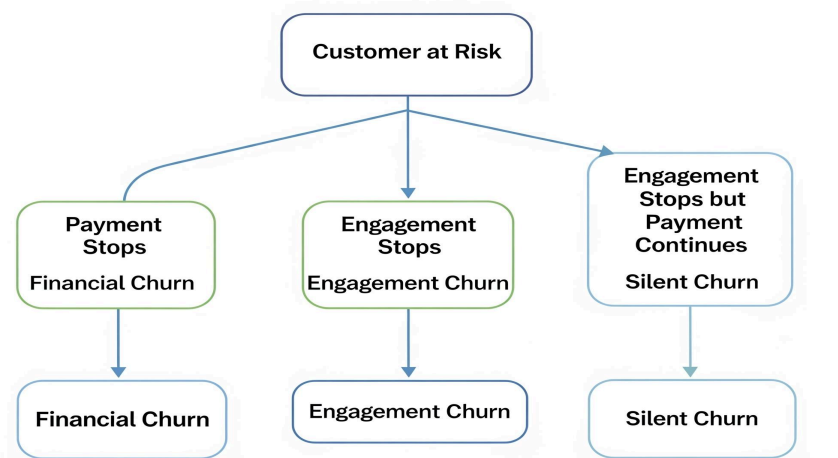
- Poor onboarding
 - Feature complexity
 - Lack of ongoing value discovery
-

Hypothesis 3: Silent Churn (Hidden Risk)

Some customers may **continue paying but stop using the product**, representing hidden churn risk that often materializes later.

This framing treats churn as a **continuum**, not a binary event.

Behavioral Churn Hypothesis Tree



4. Data & Scope

Data Sources Used

To evaluate churn holistically, the analysis combined **financial, behavioral, and subscription data**:

| Dataset | Purpose |
|---------------|--|
| Customers | Demographics, geography, identifiers |
| Subscriptions | Plan type, tenure, cancellation status |
| Transactions | Revenue behavior over time |
| User Activity | Product engagement signals |

This multi-table approach avoids misleading conclusions that arise when churn is analyzed from **only one dimension**.

5. Operational Definitions (Critical for Valid Analysis)

To ensure consistency, churn was defined using a **90-day inactivity window**, agreed upon **before analysis**.

| Churn Category | Operational Definition |
|------------------|--|
| Financial Churn | No payment in last 90 days |
| Engagement Churn | No login in last 90 days |
| Silent Churn | Payment present, but no login in 90 days |
| Healthy Customer | Paying and actively logging in |

These definitions prevent subjective interpretation and ensure analytical integrity.

6. Analysis Steps Taken

Step 1: Baseline Product Health Check

Key Metrics:

- Total customers: **50,000**
- Revenue trend: **Steady month-over-month growth**
- Engagement events: **High login and feature usage volumes**

Conclusion:

The product is **not failing globally**.

Churn is likely **behavioral and segment-specific**, not systemic.

Step 2: Revenue & Subscription Analysis

Key Findings:

- Total revenue generated: **₹51.5M+**
- Approximately **30% of subscriptions are canceled**
- Revenue is **highly concentrated among a subset of high-LTV customers**

Implication:

Retention of high-value customers has a **disproportionate impact** on business outcomes.

Step 3: Engagement Analysis

Key Findings:

- Logins and feature usage dominate user activity
- Monthly Active Users (MAU) remain stable over time

Implication:

While the product maintains strong overall engagement, **individual disengagement still exists**, warranting targeted intervention.

7. Churn Segmentation Results

Financial Churn

Customers who stopped paying in the last 90 days.

Insight:

This group represents **direct revenue loss** and is most sensitive to pricing and perceived value.

Engagement Churn

Customers who stopped logging in for 90 days.

Insight:

These users may still be subscribed but no longer perceive sufficient value, pointing to **onboarding or product adoption gaps**.

Silent Churn

Customers who continue paying but do not log in.

Result:

No silent churn users detected.

Insight:

This is a **strong positive signal**, indicating that paying customers actively use the product — a sign of solid product–value alignment.

Healthy Customers

Customers who are paying and actively using the product.

Insight:

This segment represents the **core value base** and should be protected through proactive customer success efforts.

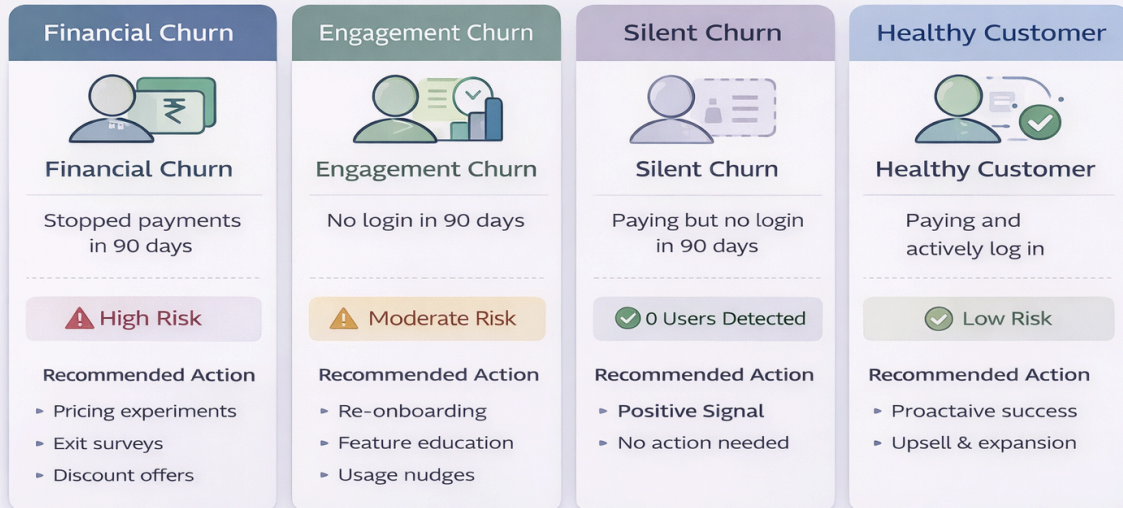
8. Final Customer Personas

Each customer was assigned **one mutually exclusive persona**:

- Financial Churn
- Engagement Churn
- Silent Churn
- Healthy Customer

This enables **persona-based decision making**, replacing one-size-fits-all retention strategies.

Customer Personas Derived from Behavioral Signals



9. Executive-Level Business Insights

- Churn is **multi-dimensional**, not binary
- Revenue loss is driven primarily by **financial churn**
- **No silent churn** indicates strong product-market fit
- A small group of customers contributes a large share of revenue
- Targeted retention is more effective than blanket interventions

10. Strategic Recommendations

Financial Churn

- Pricing experiments and discounts
- Exit surveys to capture churn drivers

Engagement Churn

- Re-onboarding flows
- Feature education campaigns
- Usage nudges

Healthy & High-LTV Customers

- Proactive customer success
 - Premium support
 - Upsell and expansion strategies
-

11. Business Impact

This analysis enables the organization to:

- Reduce churn through **behavior-specific actions**
 - Allocate resources more efficiently
 - Protect high-revenue customers
 - Shift from **reactive churn tracking to proactive retention strategy**
-

12. Conclusion

This case study demonstrates how **SQL-driven analytics**, combined with strong problem framing, can transform raw data into **clear, defensible business decisions**.

THANK YOU