Churn Prediction Case Study
Analyzing a Subscription-Based App

Problem

A subscription-based wellness app was experiencing ongoing user churn. While overall churn was visible in topline metrics, the product team lacked clarity on:
- Which user behaviors signal churn risk early enough to intervene?
- Understanding behavioral churn signals would enable the team to build targeted retention strategies instead of relying on generic engagement campaigns.

Objective

Identify the behavioral patterns most strongly associated with churn and create a simple, interpretable churn risk framework that product and lifecycle teams could use for intervention.

Data

I analyzed a weekly user snapshot dataset representing 4,000 users over multiple months. Each row captured a user's weekly behavior, including:
- Weekly sessions & total minutes
- Number of distinct features used
- Support tickets filed
- Payment failures
- Tenure (weeks since signup)
- Whether the user churned that week

Rolling 4-week aggregates were created to capture recent engagement trends.

Approach

Instead of building a black-box predictive model, I used a behavior-driven, interpretable approach focused on product decision-making.

Step 1: Define Behavioral Risk Signals

I created binary churn signals representing known retention patterns:

Signal	Definition	Why it matters
Low Activity	Very low sessions in past 4 weeks	Engagement drop often precedes churn
Inactivity Gap	≥1 week since last activity	Habit disruption is a churn precursor

Payment Issues	Recent failed payment attempts	Billing friction increases churn risk
Support Problems	Multiple support tickets	Poor experience reduces retention
Low Feature Usage	Narrow feature usage	Shallow adoption = low product value

Step 2: Compare Churn Rates by Signal

For each signal, I measured the churn rate when the signal is present
This identifies which behaviors are the strongest churn drivers.

Step 3: Build a Churn Risk Score

I combined signals into a simple scoring model:
- Activity decline and inactivity gaps weighted highest
- Payment failures and support issues weighted next
- Low feature breadth included as a supporting risk factor

Users were then grouped into Low, Medium, and High churn risk tiers based on their scores.

Key Insights

1. Engagement decline is the strongest churn predictor
   a. Users with low recent activity showed the highest churn rates.
   b. This indicates that behavioral disengagement precedes cancellation, highlighting the importance of early re-engagement.

2. Inactivity gaps are a critical warning sign
   a. Users who skipped even one full week of activity were significantly more likely to churn.
   b. This suggests the product relies on habit formation, and disruption increases churn probability.

3. Payment failures drive immediate churn risk
   a. Even a single payment failure sharply increased churn rates.
   b. This confirms the importance of frictionless billing recovery flows.

4. Support issues correlate with churn
   a. Multiple support tickets were associated with higher churn
   b. This suggests unresolved product or UX issues impact retention.

5. Risk tiers meaningfully separate users
   a. High-risk users churned at a much higher weekly rate than low-risk users.

b. This validates that simple behavioral scoring can effectively segment retention risk.

Recommendations

Based on the analysis:
- Build early re-engagement triggers
  - Trigger in-app nudges or push notifications when sessions drop below a healthy threshold.
- Monitor inactivity gaps
  - Flag users who skip a week and target them with habit-restoration prompts or personalized content.
- Improve payment recovery flows
  - Introduce smart retry logic and proactive billing alerts to reduce churn from payment failures.
- Prioritize support-driven retention
  - Route users with repeated support issues into proactive retention outreach or UX follow-up.
- Use churn risk tiers in lifecycle marketing
  - Target high-risk users with tailored retention campaigns rather than generic messaging.