

Ravenstack Churn Prediction: Low Activity Is the Strongest Leading Indicator

1. Executive Summary

Key Finding:

96.8% of churned accounts had fewer than **6 active days** (on a 30-day scale) in the full subscription month **preceding their churn**.

Secondary Signals (in that same pre-churn month):

- Downgrade occurred: **5.71%**
- Median Ticket Response Time (TTR) > 48 hours: **5.71%**
- Customer Satisfaction Score (CSAT) < 3.5: **3.53%**

False Signals Removed:

Accounts that were still in *trial* mode at the time of churn: **0%** — indicating trial status is **not** a risk signal.

2. Recommended Business Actions

Generate a **High-Risk Customer List** based on simple, interpretable rules:

- If `usage_days_m < 6` in the past 30 days → mark as **At Risk**
- If **any** of the following also occur:
`is_downgrade = 1` OR `TTR > 48h` OR `CSAT < 3.5` → mark as **High Risk**
Otherwise → **Medium Risk**

Trigger CSM Playbooks:

- High Risk: Prioritized human outreach, CSM call queue, resource allocation
- Medium Risk: Focus on product onboarding, activation and feature engagement

Embed into Weekly Automation Loop:

- Run this rule set weekly
- Refresh high-risk list
- Auto-distribute to the CSM team as a rolling priority list

3. Key Risk Signals (Chart Summary)

Signal Type	% of Churned Accounts
Active Days < 6/30	96.81%
Downgrade (<i>is_downgrade</i>)	5.71%
Median TTR > 48h	5.71%
CSAT < 3.5	3.53%
Still in Trial	0%

Part 2 – Technical Implementation & Reproducibility

4. Methodology Overview

To eliminate hindsight bias, we built a **monthly account panel** using the 5 raw files provided:

- *subscriptions.csv* used as the **monthly time anchor**
- Merged with: *feature_usage.csv*, *support_tickets.csv*, *churn_events.csv*, and *accounts.csv*

Observation Windows:

- For churned accounts: The **full subscription month BEFORE churn**
- For all accounts: The **latest available full month**

Key Feature Definitions:

- *usage_days_m*: Count of distinct active days in *feature_usage*
 - *is_downgrade*: Flag from *subscriptions.csv*
 - *ttr_p50_m*: Median ticket response time per month (from *support_tickets*)
 - *csat_m*: Average CSAT in that month
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5. Risk Scoring Logic (Deployment Ready)

```
if usage_days_m < 6:  
    if is_downgrade == 1 or ttr_p50_m > 48 or csat_m < 3.5:  
        risk_score = 'High'  
    else:  
        risk_score = 'Medium'
```

else:
 risk_score = 'Low'

Interpretation:

- **High Risk:** Requires CSM urgent attention
 - **Medium Risk:** Focus on activation/product education
 - **Low Risk:** No action needed; continue monitoring
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6. Data Traceability & Deliverables

- **high_risk_accounts.csv:** Full list of Medium/High Risk accounts with fields: `account_id`, `mrr`, `usage_days_m`, `downgrade`, `ttr`, `csat`, `risk_score`
 - **high_risk_top20.csv:** Top 20 high-risk accounts ranked by $MRR \times Risk\ Level$
 - **Data validation:** $ARR \approx 12 \times MRR$ was 100% consistent in `subscriptions.csv`
 - **Code reproducibility:** Core logic implemented in reproducible pandas snippets (attached in README)
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7. Next Questions for Real-World Deployment

If this were a real SaaS client scenario, we would recommend further investigation into:

Root Causes of Low Activity:

Is it due to poor onboarding, insufficient product value, seasonal drop-off, or UX friction?

Feature Usage Segmentation:

Can we build deeper metrics like "sticky features" or "module engagement" to improve signal precision?

Segment-Level Risk Factors:

Are certain industries, countries, or referral channels more prone to low usage AND downgrade?