AI Automation / CRM Automation

Define and calculate health scores from CRM data — engagement, support tickets, payment history, usage — predicts churn before it happens.
Difficulty: Advanced
Model: GPT-4 / Claude / Gemini
Use Case: Customer Success, Churn Prediction
Updated: May 2026
Why This Prompt Exists
Customer health scores are either manual (impossible at scale) or black-box (nobody trusts them). The right approach is a transparent, data-driven score that predicts churn risk.

You get:

- churn surprises — customers leave with no warning
- manual health checks — CSMs spend hours reviewing accounts
- inconsistent scoring — each CSM has their own definition of “healthy”
- no early warning system — intervention happens after churn, not before
- black-box scores — nobody knows why a score is low, so nobody acts

But health scores can be systematic:

- product usage: login frequency, feature adoption, session duration
- support health: ticket volume, resolution time, satisfaction rating
- payment health: on-time payments, credit card declines, past due
- engagement: email opens, meeting attendance, NPS responses
- relationship: account executive tenure, executive sponsorship

Without scores, you manage by gut feel.

This prompt designs transparent, actionable health scores.

The Prompt

```
Assume the role of a customer success architect who designs health scores.

Your task is to create a health score formula from available CRM data.

Generate:

1. HEALTH DIMENSIONS

| Dimension | Weight | Data Source | Scoring Logic |
|-----------|--------|-------------|---------------|
| Product Usage | 40% | Product analytics | Daily active users, feature adoption |
| Support Health | 20% | Support ticket system | Tickets/week, resolution time, CSAT |
| Payment Health | 20% | Billing system | On-time payments, past due days |
| Engagement | 10% | CRM | Meeting attendance, email responses |
| Relationship | 10% | CRM | Executive sponsor, account tenure |

2. SCORING LOGIC PER DIMENSION

**Product Usage (40% of total)**
- Daily active users (0-10 points): 0 users → 0 pts, 10+ users → 10 pts
```

- Features adopted (0-10 points): out of 5 key features, 2 pts each
- Session duration (0-10 points): <5 min → 0 pts, >30 min → 10 pts

Support Health (20% of total)
- Tickets per week (0-10 points): 0 tickets → 10 pts, 5+ tickets → 0 pts
- Resolution time (0-10 points): <1 day → 10 pts, >5 days → 0 pts

Payment Health (20% of total)
- Payment status (0-10 points): on-time → 10 pts, 30+ days past due → 0 pts
- Decline history (0-10 points): no declines → 10 pts, 3+ declines → 0 pts

Engagement (10% of total)
- Meeting attendance (0-10 points): 100% attended → 10 pts, 0% → 0 pts
- Email response rate (0-10 points): >80% → 10 pts, <20% → 0 pts

Relationship (10% of total)
- Executive sponsor (0-10 points): active sponsor → 10 pts, none → 0 pts
- Account tenure (0-10 points): >2 years → 10 pts, <3 months → 0 pts

3. HEALTH SCORE FORMULA

```
Health Score =
  (Usage_Score × 0.4) +
  (Support_Score × 0.2) +
```

```
  (Payment_Score × 0.2) +
  (Engagement_Score × 0.1) +
  (Relationship_Score × 0.1)
```

Score ranges:
- 80-100: Green (Healthy)
- 50-79: Yellow (At Risk)
- 0-49: Red (Critical)

4. TREND COMPONENT
   - Score trend: Improving / Stable / Declining (over 90 days)
   - Velocity matters: declining from 85 to 65 is more urgent than stable at 55

5. ALERT TRIGGERS
   - Score drops >15 points in 30 days → Alert CSM
   - Score falls below 50 → Schedule QBR immediately
   - Payment dimension = 0 → Flag for collections

6. SCORE COMPONENTS BREAKDOWN (for CSM)

```json
{
  "customer_name": "Acme Inc",
  "total_score": 72,
  "status": "Yellow",
  "components": {
    "usage": 85,
```

```
    "support": 60,
    "payment": 90,
    "engagement": 70,
    "relationship": 55
  },
  "trend": "declining",
  "primary_risk": "low relationship score"
}
```

7. ACTION RECOMMENDATIONS

- Low usage → Schedule training, share best practices
- Low support → Review open tickets, identify root cause
- Low payment → Check billing issues, offer payment plan
- Low engagement → Executive business review (QBR)
- Low relationship → Assign executive sponsor

INPUTS:

Available data sources:

[PASTE DATA SOURCES]

Historical churn drivers:

[PASTE HISTORICAL ANALYSIS]

Team capacity:

[PASTE TEAM CAPACITY]

Weight preferences:

```
[PASTE WEIGHT PREFERENCES]

RULES:
- Weigh dimensions by their correlation with churn (use historical
data)
- Make scores transparent (CSMs should know why a score is low)
- Track trends, not just point-in-time (declining score needs
intervention)
- Automate data collection (manual scoring doesn't scale)
- Test scores on historical churn (do low scores predict churn?)
- Review weights quarterly (churn drivers change over time)
- Don't create alerts for every fluctuation (alert fatigue)
```

How To Use It

- Weigh dimensions by their correlation with churn — use historical churn analysis to set weights.
- Make scores transparent — CSMs should understand why a score is low (components breakdown).
- Track trends, not just point-in-time — a declining score needs intervention even if still “green.”
- Automate data collection — manual health scoring doesn’t scale beyond 50 customers.
- Test scores on historical churn data — do low scores actually predict churn?
- Review weights quarterly — churn drivers change as your product and market evolve.
- Don’t create alerts for every small fluctuation — prevent alert fatigue.

Example Input

Available data sources:
“Product analytics (DAU, feature usage), Zendesk (tickets, CSAT), Stripe (payment status), Salesforce (meeting logs, emails)”

Historical churn drivers:
"85% of churned customers had <3 logins per week for 30+ days; 70% had >5 support tickets in last 90 days"

Team capacity:
"10 CSMs, 800 customers, 3 QBRs per week per CSM"

Weight preferences:
"Product usage is our strongest retention lever; support issues are often product-related"

Why It Works

Most health scores are either gut feelings ("seems fine") or black-box algorithms ("model says 43% churn risk"). Neither drives action.

This framework improves outcomes by forcing:

- health dimension identification (what predicts churn?)
- weight specification (how important is each dimension?)
- scoring logic (how to calculate each component?)
- trend tracking (declining score needs intervention)
- action recommendations (what to do for each risk factor?)

Failure modes this prevents:

- Churn surprises — customer leaves with no warning signs flagged
- Manual health checks — CSMs spend 10 hours/week on manual scoring
- Inconsistent intervention — high-risk accounts get missed
- No action guidance — low score triggers no specific next step

This improves on: Intuitive health assessment ("I think they're happy") and black-box scores. Transparent scores drive specific actions.

Related to: CRM-02 (Health Scanner) for opportunity risk; CRM-03 (Summarizer) for capturing health signals from conversations.

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