

# Beyond Surveys: Real-Time User Satisfaction Prediction with LLMs and Telemetry

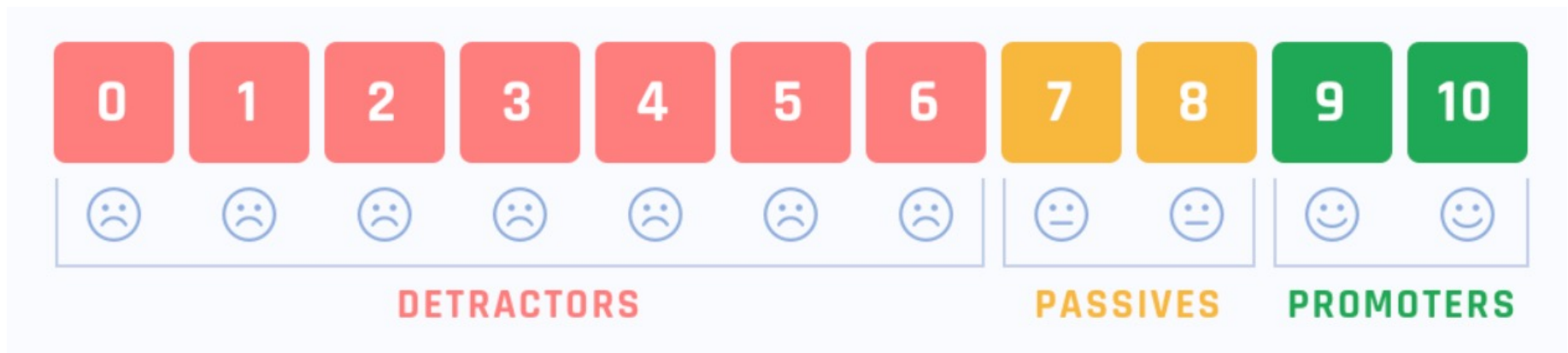
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Conf42 Machine Learning 2026

## What is Net Promoter Score (NPS)?

- Industry-standard metric for measuring customer loyalty
- One simple question: “How likely are you to recommend us?”
- 0–10 rating → Detractors, Passives, Promoters



# How NPS is calculated?

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## **-100 to 0: POOR**

- More Detractors than Promoters.
- Brand reputation is at risk.

## **1 to 30: GOOD**

- Solid foundation.
- Focus on converting Passives to Promoters.

## **31 to 70: GREAT**

- Strong customer loyalty.
- Your brand is a market leader.

## **71 to 100: WORLD-CLASS**

- Customers are your primary marketing engine.



$$\text{NPS} = \% \text{ Promoters} - \% \text{ Detractors}$$

$$\text{NPS} = 70\% - 10\% = 60$$

Range: -100 to +100

# How Companies Collect NPS Today

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## **Email Surveys**

The Industry Standard

## **In-App Popups**

Real-Time Engagement.

## **SMS Surveys**

High-Speed Response.

**Manual Follow-ups** White-Glove Service.



**Email Surveys**



**In-App Popups**



**SMS Surveys:**

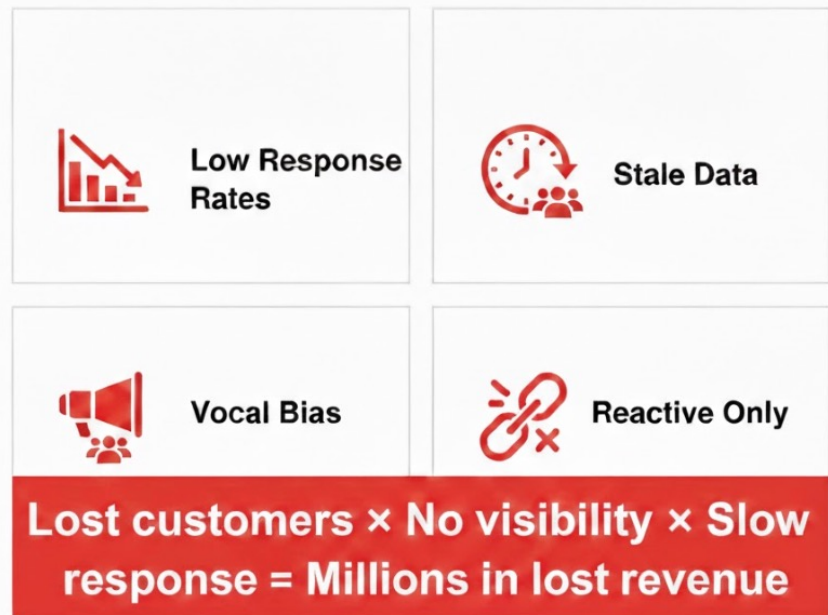


**Manual Follow-ups**

# The Industry Problem

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- **The Participation Gap:** Response rates are stuck between **1–5%**. Most users are "silent."
- **The Speed Barrier:** Data is often **stale**. Insights arrive days or weeks after the interaction.
- **Extreme Bias:** Only the "vocal minority" respond—the extremely happy or the very angry.
- **Reactive, Not Proactive:** By the time you see the score, you've already missed the window to fix the issue.



# The Opportunity

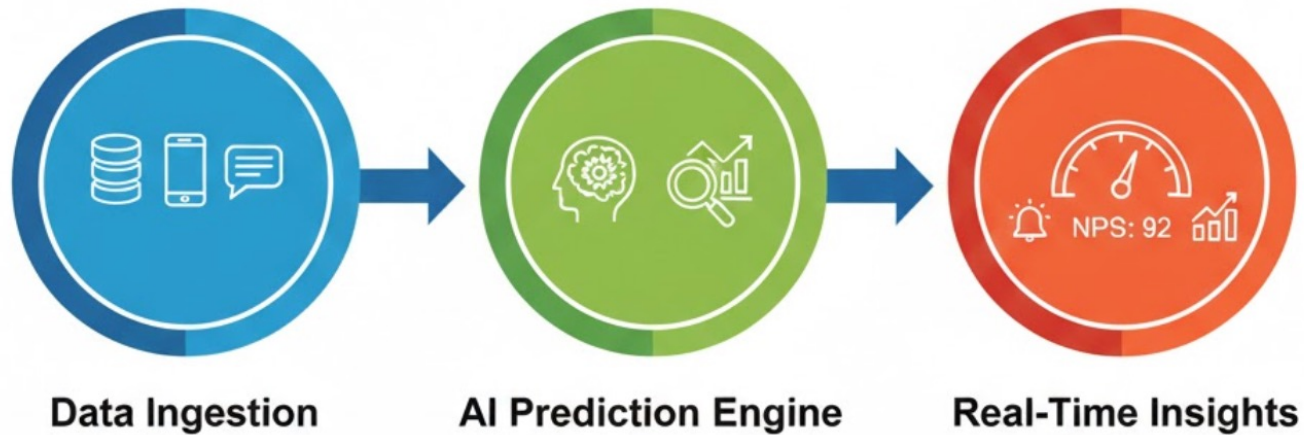
What if we could eliminate surveys?  
What if we could know user sentiment instantly?  
What if we could predict NPS?



# Introducing DNPS: Dynamic Net Promoter Score

AI model that predicts user sentiment using:

- Telemetry
- Behavioral analytics
- Session patterns
- Machine learning



# Data Collection

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- **Behavioral Interaction Data**

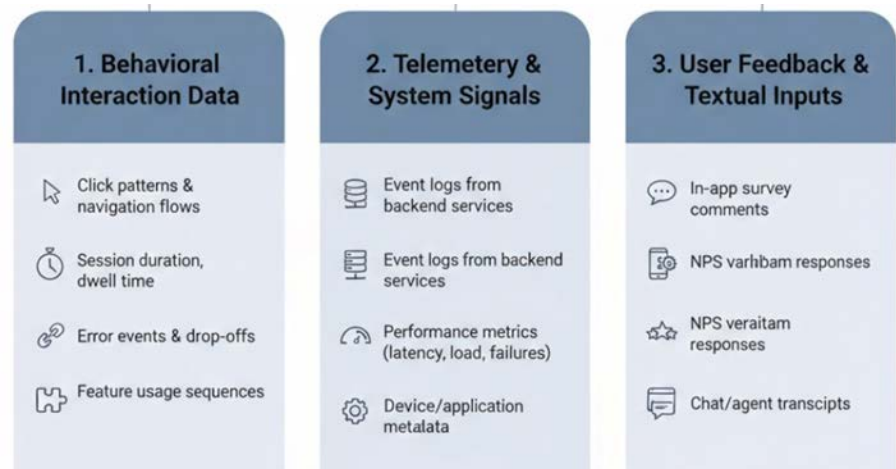
what users are doing and how they behave during a session

- **Telemetry & System Signals**

how the system is performing while the user is interacting with it.

- **User Feedback & Textual Inputs**

how users feel and what they're saying in their own words.



# Data Processing

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- **Data Cleaning**

Removes noise, duplicates, and incomplete records.

- **Normalization & Structuring**

Converts raw inputs into consistent, usable formats.

- **Timestamp Alignment**

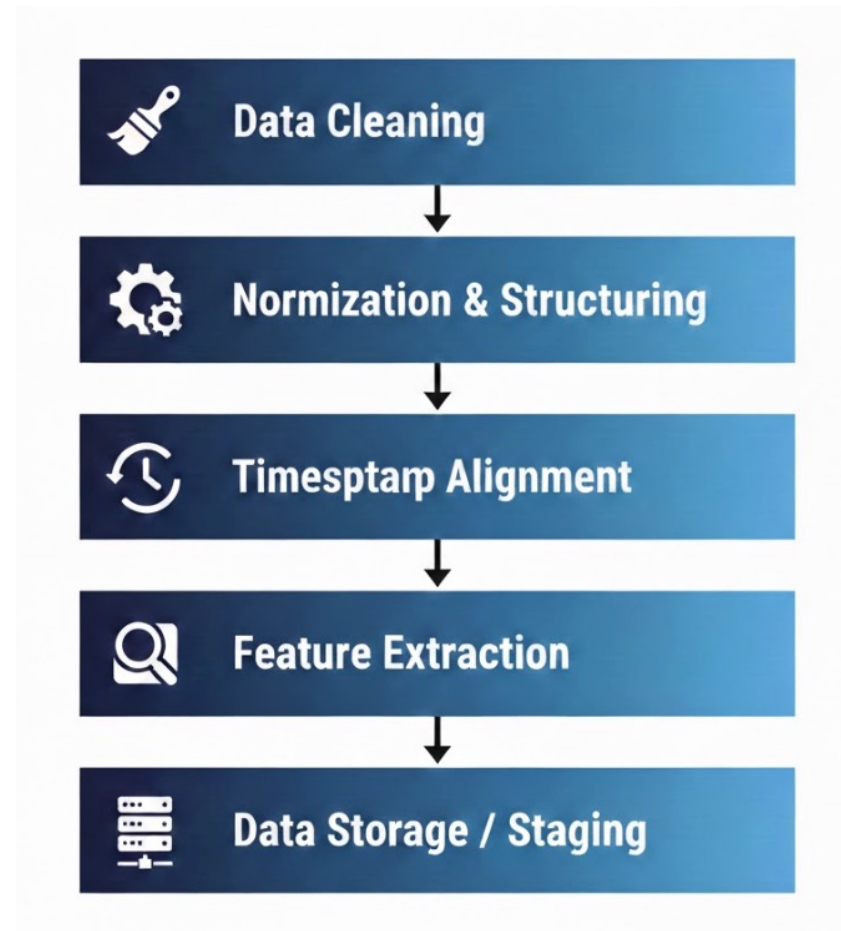
Lines up events from different sources in the correct order.

- **Feature Extraction**

Pulls key signals like patterns, metrics, and text embeddings.

- **Data Storage / Staging**

Holds processed data for model training and real-time scoring.



# Hybrid AI Modeling - Overview

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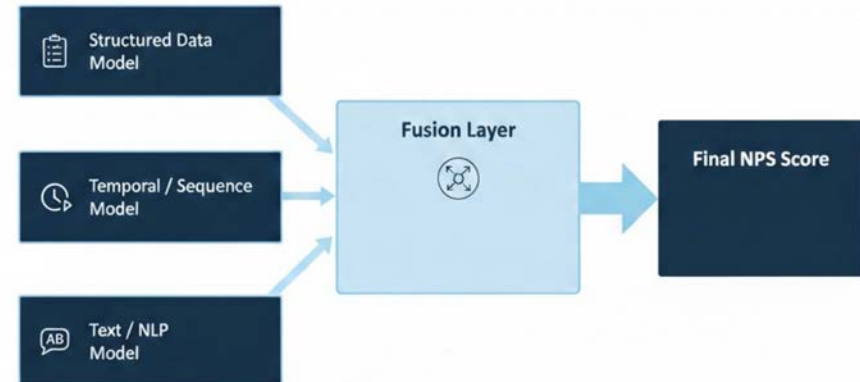
Combines multiple AI models to predict dynamic NPS scores by leveraging all types of input data

**Multi-model approach** ensures high accuracy

**Handles different data types:** structured metrics, behavioral sequences, and text feedback

**Fusion** produces a single, robust prediction

**Supports explainability:** each input's contribution can be analyzed



# Hybrid AI Modeling - Model Details

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## Structured Data Model

Uses numerical and categorical features from behavioral & telemetry data

Example: Gradient Boosted Trees (XGBoost, LightGBM)

Detects patterns like feature usage impact on NPS

## Temporal / Sequence Model

Uses sequential behavior data (clicks, sessions, events)

Example: LSTM or Transformer

Captures trends and user behavior over time

## Text / NLP Model

Uses user comments and survey responses

Example: BERT embeddings or other LLM-based text vectors

Extracts sentiment, topics, and context



Structured Data Model



Temporal Model



Text / NLP Model

# Fusion Layer – Combining AI Insights

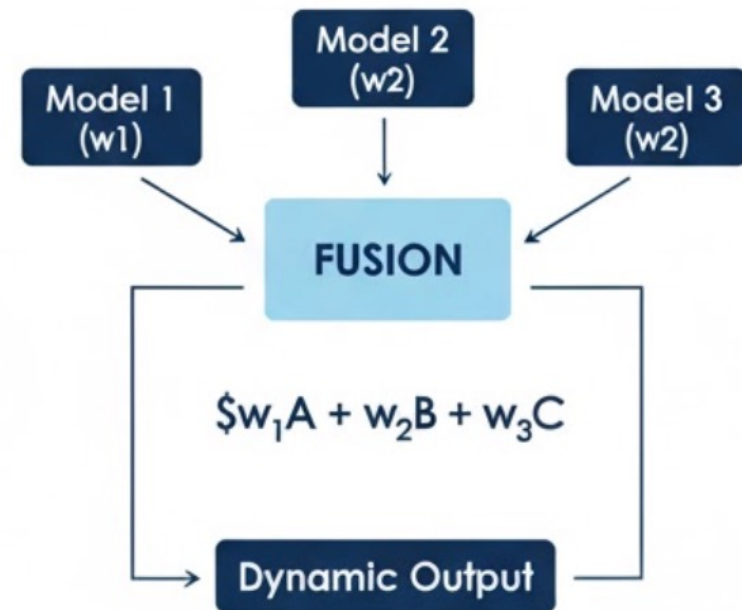
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Collects outputs from **structured, temporal, and text models**

**Learns to weight** each input based on its importance for the prediction

**Does not treat all data equally** — prioritizes the most relevant signals

## WEIGHTED ENSEMBLE



# Fusion Layer – Explainable AI (XAI)

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**Clarifies why a prediction was made** by showing which features or behaviors influenced the NPS score.



**Uses SHAP and LIME** to break down the model output into human-readable explanations.



**Improves trust and transparency** so stakeholders understand the reasoning behind AI decisions.



**Helps with debugging and validation** by revealing unexpected or incorrect model behavior.



**Supports compliance and audit needs** by providing clear justification for each prediction.



XAI increases confidence by showing how and why predictions are made.

# Prediction & Interpretation

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Produces the final **dynamic NPS score**

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Provides the **confidence level** of the prediction

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Shows **root-cause factors** affecting the score

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Suggests **actionable recommendations**

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Delivers insights through **business dashboards**

# Prediction Results & Model Performance

Proposed **DNPS hybrid model** achieves **~85.9% accuracy**, outperforming all baselines

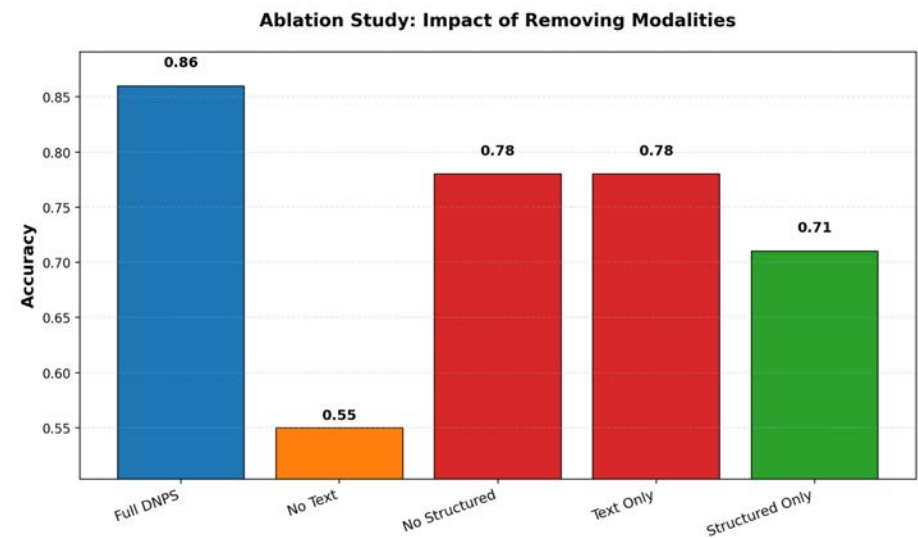
Lower error: **MAE ~1.21**, strong F1 score

**Multi-modal fusion** (behavior + telemetry + text) performs far better than single-modality models

Ablation shows the importance of each data type:

- Removing text: accuracy drops to **~55%**
- Removing behavioral/telemetry: drops to **~78%**

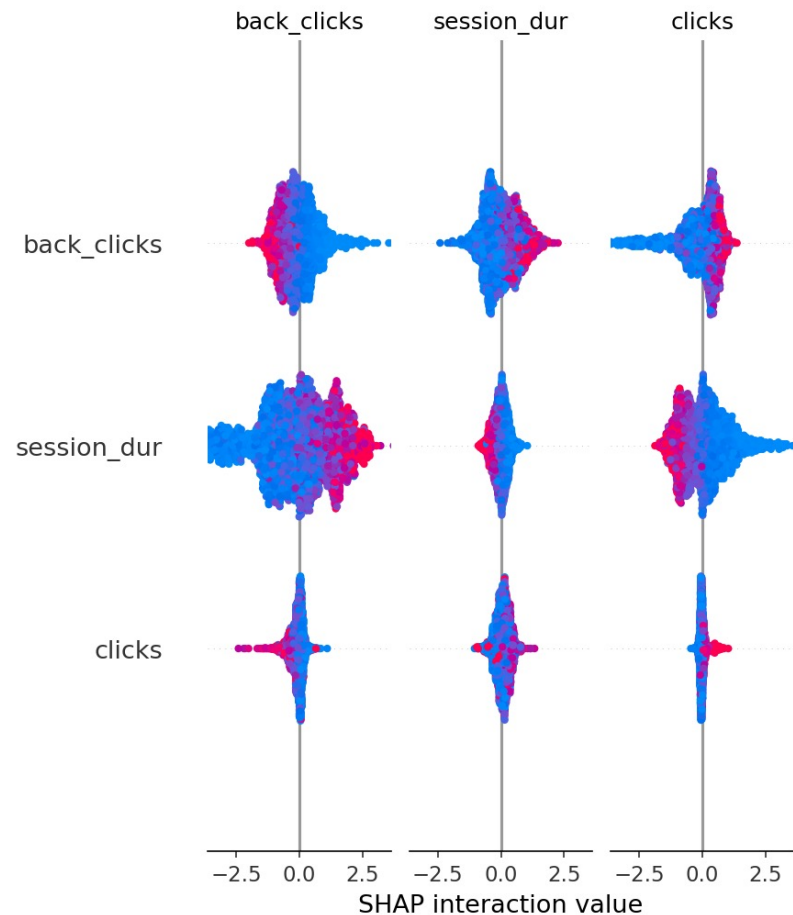
Real-time inference runs in **~80 ms**, supporting live dashboards and operational use



# Explainability, Insights & Business Value

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- SHAP/LIME analysis reveals **top drivers** of NPS:
  - High **back-clicks** → strong negative impact
  - **Short session duration** → lower satisfaction
  - High **click activity** → promoter behavior
- Provides **root-cause insights** such as buffering issues or negative feedback patterns
- Helps teams make **proactive decisions** (feature fixes, UX improvements)
- Reduces dependence on surveys by providing **continuous, dynamic NPS**
- Enables **business dashboards** with real-time predictions and explanations



# Limitations & Future Work

## **Limitations**

- Requires large, high-quality datasets
- Cold-start issues for new users
- Hybrid model complexity
- Possible bias in text feedback

## **Future Work**

- Add more diverse data sources
- Use advanced transformer-based models
- Improve cold-start handling
- Enhance real-time explainability

Thank You

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