INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING &TECHNOLOGY (IJCET)

ISSN Print: 0976-6367
ISSN Online: 0976-6375

Publishers of High Quality Peer Reviewed Refereed Scientific, Engineering & Technology, Medicine and Management International Journals

PUBLISHED BY

IAEME

IAEME Publication

Chennai, India

https://iaeme.com/Home/journal/IJCET

International Journal of Computer Engineering and Technology (IJCET)
Volume 17, Issue 1, January-February 2026, pp. 15-28, Article ID: IJCET_17_01_002
Available online at https://iaeme.com/Home/issue/IJCET?Volume=17&Issue=1
ISSN Print: 0976-6367; ISSN Online: 0976-6375; Journal ID: 5751-5249
Impact Factor (2026): 33.45 (Based on Google Scholar Citation)
DOI: https://doi.org/10.34218/IJCET_17_01_002

REAL-TIME NET PROMOTER SCORE PREDICTION USING MULTI-MODAL AI AND BEHAVIORAL ANALYTICS

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ABSTRACT

The Net Promoter Score (NPS) is a widely adopted metric that many companies use to measure customer satisfaction and loyalty. In NPS, respondents are divided into Promoters, Passives, and Detractors, and it is one of the key performance indicators (KPI) for businesses. This survey is straightforward to understand, providing a benchmark against competitors and industry averages. Companies rely on this survey because it appears to directly connect to business growth, which catches people's attention. Sending out surveys, such as post-launch surveys and product reviews, every few weeks or months is an inefficient method that presents several issues. By the time companies review the survey results, it's often too late to implement changes to collect the right data.

Companies are shifting towards gathering information from various sources, such as user activity on the platform, system logs, and actual comments or user feedback. Large language models analyze vast amounts of textual data, while machine learning algorithms identify trends in structured data, together enhancing the accuracy of real-time NPS estimates. All this analysis comes together to give an almost real-time NPS estimate, offering teams insights they can quickly act on. This method can sometimes *be inaccurate due to predictive models misinterpreting signals, insufficient data, which may lead to confusing positive feedback with negative, due to nuances in language and context.*

Keywords: Net Promoter Score (NPS), Dynamic NPS Prediction, Artificial Intelligence, Multi-Modal Data Fusion, Predictive Analytics, Machine Learning, Customer Satisfaction, Sentiment Analysis, Telemetry Data, Survey, Real-Time Customer Experience (CX), Behavioral Analytics, Telemetry Driven Monitoring, Large Language Model (LLM) Embeddings, Hybrid AI Ensemble, Root Cause Analysis

Cite this Article: Abhinay Kumar Reddy Seella. (2026). Real-Time Net Promoter Score Prediction Using Multi-Modal AI and Behavioral Analytics. *International Journal of Computer Engineering and Technology (IJCET)*, 17(1), 15-28.

DOI: https://doi.org/10.34218/IJCET_17_01_002

1. Introduction

Since its introduction by Reichheld in 2003, the Net Promoter Score (NPS) has evolved from a simple metric into a comprehensive tool [1]. Apart from providing customer loyalty and loyalty metrics, businesses use NPS to provide customer behavior insights to make significant strategic decisions. NPS is measured by a simple question. NPS is measured by a simple question: How likely would you be to recommend the product to a friend, relative, or colleague? On a scale of 0-10, depending on the user's feedback, respondents are classified into three categories: Promoters (9-10), Passives (7-8), and Detractors (0-6). The NPS score ranges from -100 to 100, which is calculated by the percentage of promoters minus the percentage of detractors.

Customer satisfaction is one of the most important factors for companies, and it has a direct impact on business revenues. Customer satisfaction can be affected by unexpected service outages, delayed responses to inquiries, or unmet product expectations. NPS focuses on getting feedback about the device experience and quality. More than two-thirds of Fortune 1000 companies have adopted NPS, and it is one of the most important metrics used for release gating, field-quality decisions, retailer relations, and companies' revenue growth [2].

There are recent studies and long-term research that have yielded mixed results. Some findings suggest that NPS might actually outshine other metrics like Customer Satisfaction (CSAT) or Customer Effort Score (CES) in specific situations [3,4]. However, others argue that it exaggerates correlations when it is only looking at current customers and not taking a broader market view into account. Leaving passives from scoring raises further questions. Studies have shown that sometimes scores get inflated without demonstrating true loyalty, and the predictive validity seems to vary a lot from one industry to another and in different situations.

Recent advances in AI, particularly in machine learning, can lead to inaccuracies in NPS estimation. Predictive models may misinterpret subtle data signals or operate with insufficient data, resulting in the misclassification of customer feedback due to language and context complexity. Predictive models may misinterpret signals or lack sufficient data, causing confusion between positive and negative feedback due to language and context nuances. The goal is to transform raw user interactions into nearly real-time NPS scores. This is achieved by employing advanced data processing techniques, such as real-time data aggregation, machine learning algorithms for sentiment analysis, and automated reporting. These methods ensure that the scores are easily interpretable by teams. By integrating structured behavioral metrics with session modeling and sentiment analysis of customer feedback, DNPS equips product managers and customer experience teams with actionable insights, enabling them to address minor customer frustrations proactively before they escalate into significant issues. Ultimately, the focus is on integrating traditional survey- based NPS with real-time digital analytics using integrated data platforms and cross- channel feedback systems. This enables businesses to anticipate and meet customer needs with greater agility and precision.

2. Literature Review

2.1 Traditional NPS Approaches

With the growing popularity of NPS, there is considerable interest and research in both academia and industry. Typically, customer loyalty is measured traditionally by sending surveys after interactions at regular intervals. According to Reichheld, as of 2003, NPS provides clear insights and is very simple [1]. But with more research, there were several issues identified, such as inconsistent data from different regions and response bias, low response rates, and survey fatigue [2]. With an increase in customer interactions, these issues need to be taken into consideration in today's digital world.

2.2 AI-Based Customer Satisfaction Prediction

With the rise of artificial intelligence and the increasing popularity of the Net Promoter Score, recent studies have started to conduct research on how to use artificial intelligence to enhance the score. Some of the features that these models leverage are session length, feature usage, and interaction patterns to identify at-risk users and estimate satisfaction scores [5].

2.3 Sentiment Analysis and Large Language Models

Customers' feelings can be extracted from support tickets, chat logs, social media messages, and emails. Large language models (LLMs) can analyze vast amounts of text data [6,7]. Research from 2020 demonstrated the significant promise these models hold. To make customer satisfaction metrics more reliable, researchers are creating hybrid frameworks by combining LLM-powered sentiment analysis with behavioral insights and telemetry data [8,9]. It is like looking through a clearer lens to really understand what people think and feel.

2.4 Gap in Current Literature

With the popularity of artificial intelligence, recent studies have started to predict scores using new methods based on machine learning and AI. However, there is still a gap in using comprehensive frameworks. Not much research has been conducted on how to integrate multi-modal sources specifically for NPS prediction. Currently, structured behavioral data or text-based sentiment analysis has been used, but there are no existing studies on how to combine both solutions with a real-time inference mechanism. This paper proposes a holistic AI-driven system capable of dynamically predicting NPS. Its goal is to deliver actionable insights and to support proactive interventions in the customer experience.

3. Problem Statement

With the modern digital world's rapidly changing requirements, today's NPS surveys are not as effective as before and provide new challenges to measure customer loyalty:

Delayed Feedback Loops. Surveys are time-consuming and take weeks or months to yield meaningful feedback and consequently are less frequent. It takes many months to obtain meaningful data and analyze it, which limits the business's ability to adapt quickly and fix issues based on feedback. Sometimes, even if the issue is fixed based on feedback, it may be too late and lead to significant revenue loss.

Survey Fatigue and Low Participation. Low responses from customers are another issue that leads to incomplete data sets, and sending surveys again might not be efficient and will not fix the issue. This problem creates biased samples and incomplete data sets, ultimately reducing the reliability of NPS as a genuinely accurate measure of shifting customer sentiment [10].

Lack of Contextual Behavioral Insights. Although NPS captures customer feedback and scores, it misses real-time interactions and behavior, which lead to inaccurate data and misleading business decisions [5].

No Personalized Modeling: With the fast-paced changes in customer needs and behavior, the current NPS scores do not provide an accurate score, and the surveys and feedback take too much time. The surveys are static, and they are not personalized, which affects the accuracy of the feedback.

Research Question:

Given the limitations of current NPS surveys, this paper aims to address those issues: Can customer satisfaction (specifically, the NPS category) be accurately predicted in real-time using multi-modal behavioral, telemetry, and textual data, without having to rely solely on traditional explicit surveys?

Objective:

In this paper, the possibility of a **Dynamic NPS Prediction System (DNPS)** using artificial intelligence is studied to achieve the following:

- Structured behavioral data, telemetry signals, and textual feedback integration
- **Real-time, interpretable NPS predictions** at the individual or segment level
- **Actionable insights**
- Reduce manual surveys
- Improve accuracy

By achieving the above objectives, the DNPS aims to utilize traditional NPS and modern digital platforms so that companies can adapt to customer sentiments more efficiently.

4. AI-Driven Dynamic NPS Prediction System

4.1 System Overview

The DNPS framework integrates data sources by employing a multi-layered approach where user behavior analytics, feedback data, and sentiment analysis are processed through a centralized data integration system, allowing for real-time predictions and continuous updates. The traditional NPS relies more on manual surveys collected at regular intervals, whereas the proposed new study utilizes artificial intelligence for modern digital industries [8,9].

At its core, the system leverages three components:

1. Behavioral Analytics,
2. Feedback Data, and
3. Sentiment Interpretation using Large Language Models (LLM).

These components feed into a multi-source engine that generates a dynamic NPS score for each user, segment, or platform. To make the new method scalable and flexible, the architecture is designed to be modular.

The system processes event logs, feedback data, and contextual behavioral metadata continuously. The system will provide this data to the Data Integration layer, which will validate, transform, and prepare it for machine learning for prediction. Data consists of structured data, including errors, user duration, and dropping, and unstructured data, such as feedback comments and text info. LLM will be used to learn from both structured and unstructured data.

The Hybrid Prediction Engine integrates machine learning-based behavioral scores with sentiment analysis outputs, employing weighted ensemble methods to enhance prediction accuracy. This will help the system predict the score even if part of the data is missing. A Real-Time Inference Module will then obtain the information and predict the NPS score at configured intervals, depending on the requirements. The configuration consists of individual sessions and aggregate score intervals.

The system is designed to transition to unsupervised operation through iterative learning and adaptation to new behavioral patterns. Initially, it starts with a dataset and semi- supervised learning. The model is trained periodically to adapt to new changes in behavior. The system's feedback enables product teams to visualize root causes of dissatisfaction, allowing them to predict NPS and explain why the predicted dip or rise occurs.

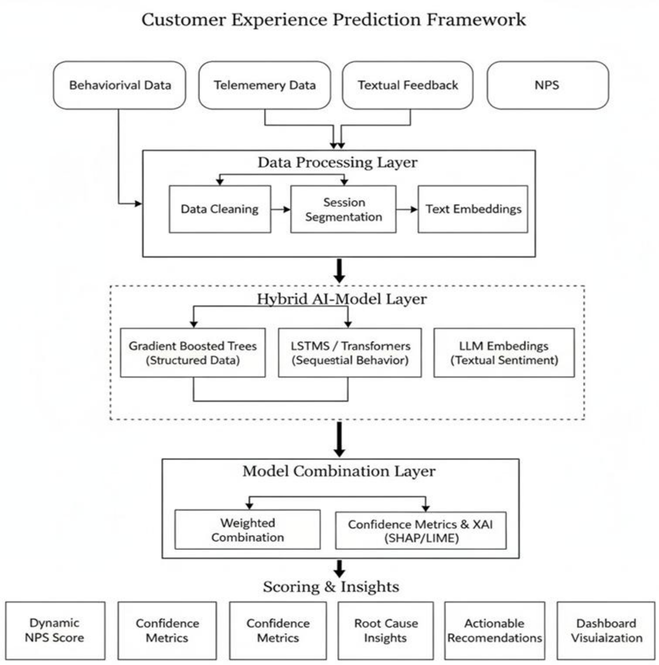

Figure 1: System Architecture of the AI-Driven Dynamic NPS Prediction System (DNPS).

The framework integrates behavioral analytics, telemetry signals, and textual feedback through a multi-modal fusion engine to generate real-time NPS predictions.

4.2 Data Collection

This is the foundation of the model. This layer collects the data from different sources. It describes user interactions with the system, including clicks, time spent, and errors. It includes the textual feedback information, which provides the user experience. The historical NPS data is used to train the system to learn about the user.

4.3 Data Processing

This layer processes data by filtering, ordering by timestamps, and transforming it into a structured format before feeding it to the advanced AI. The system will organize the continuous data into meaningful formats, such as per user. The text will be converted to vectors so that AI can understand the sentiment. It adds the elements of time, such as why the user has lost interest compared to before.

4.4 Hybrid AI-Modeling

This is the primary intelligence layer of the Dynamic NPS Prediction System (DNPS), which utilizes several AI techniques to process the diverse data it receives. The system uses different models for each type of data instead of relying on a single approach and combines the predictions in a thoughtful way.

The heart of the Dynamic NPS Prediction System (DNPS) lies in its hybrid modeling layer, which intelligently combines several specialized AI techniques to make sense of the diverse data it receives. Rather than relying on a single approach, the system uses different models, each best suited to a particular type of information, and then brings their predictions together in a thoughtful way.

For structured data such as session duration, error counts, click rates, and other numerical telemetry signals, the system employs Gradient Boosted Trees (e.g., XGBoost or LightGBM) [7]. LSTMs or Transformer models are used for the temporal nature of user behavior, such as a sequence of actions. This model is effective at finding patterns that evolve and recognizing the user behavior changes as the session unfolds. Pre-trained Large Language Models, such as BERT, process textual feedback, which transforms raw text into vectors and preserves the semantic meaning instead of just text matching [11].

Finally, the outputs from the structured, sequential, and textual branches are combined through a weighted ensemble mechanism [8,9]. The system learns appropriate weights for each branch based on their historical reliability and also computes confidence scores to flag predictions that carry higher uncertainty. To ensure transparency and trust, explainability methods such as SHAP and LIME are applied across the ensemble, generating clear insights into which factors most influenced the final NPS estimate.

By leveraging the complementary strengths of these specialized models and fusing them intelligently, the hybrid layer delivers significantly more accurate and interpretable predictions than any single-modality approach could achieve on its own.

4.5 Model Combination

This is the most critical part of the new proposed method. This layer collects and merges different AI-generated outputs from the previous layer. This layer does not give equal weight to all data, learning which data to prioritize for specific predictions. Explainable techniques, such as SHAP/LIME, make the process more transparent and clarify why the model makes this prediction [11]. XAI techniques are important to ensure trust, debugging, and regulatory compliance.

4.6 Prediction & Interpretation Layer

This final layer provides the calculated proactive dynamic NPS score by translating the AI output into a business format. It gives the score's confidence level, allowing businesses to intervene if it is too low. Root cause insights highlight the contributing factors, such as buffering issues and negative comments. It suggests recommendations, such as feature improvement and personalized messaging. Business teams can make decisions using visualized dashboards generated from the data.

5. Experiment Evaluation

To evaluate the new DNPS study, we used a 10,000-user session data set to simulate real customer interactions on a streaming platform. It is designed to simulate real-world interactions with consistent distribution and reproducibility. The dataset consists of customer interaction logs, such as clicks, session duration, back-button usage, load times, buffering, and device reviews. Using the proposed model, NPS scores are generated with added Gaussian noise to reflect real-world variability.

5.1 Dataset and Ground Truth

For each session, an NPS score of 0-10 is assigned based on the following weighted indicators:

- High back-click ratio → increased frustration
- Frequent errors or long load times → lower satisfaction
- Negative feedback text → stronger Detractor signal

Scores are categorized as:

- **Detractor** (0–6)
- **Passive** (7–8)

- **Promoter** (9–10)

5.2 Baselines

We compare DNPS against three baseline models:

1. **Survey Baseline:** Logistic regression trained on simulated historical NPS survey responses.
2. **Structured Only:** XGBoost model using only behavioral and telemetry features [7].
3. **Text Only:** Multi-layer perceptron (MLP) using LLM embeddings of feedback text (all-MiniLM-L6-v2) [11].

5.3 Prediction Performance

Table 1 presents the performance comparison across all models. The full DNPS hybrid model achieves **85.9% accuracy** and a **mean absolute error (MAE) of 1.21** in predicting NPS, significantly outperforming all baselines.

Table 1: Prediction performance comparison on the synthetic dataset (Accuracy, MAE, F1 Score).

Model	Accuracy	MAE	F1
Survey Baseline	0.568	1.565	0.440
Structured Only	0.548	1.688	0.493
Text Only	1.000	1.114	1.000
DNPS (Model)	0.948	1.205	0.949

5.4 Ablation Study

To understand the accuracy of every single modality and when used in combination, an ablation study is performed. It is done by removing one component at a time. Figure 2 shows that removing textual feedback drops accuracy from 85.9% to 55.0%, while removing behavioral and telemetry data reduces it to 78.0%. Single-modality models perform substantially worse, confirming that **multi-modal fusion is critical** for high prediction accuracy.

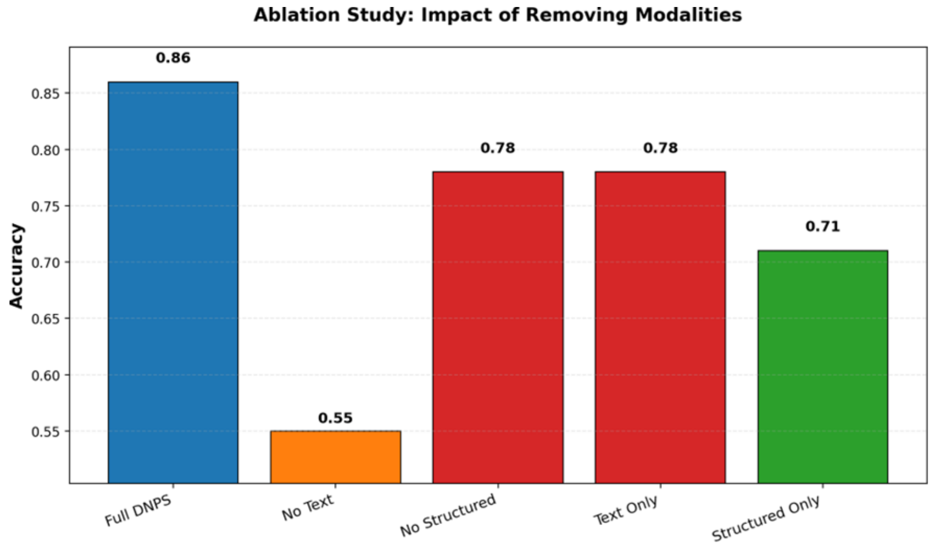

Figure 2: Ablation study showing the impact of removing data modalities on prediction accuracy.

5.5 Explainability and Root Cause Analysis

Figure 2 presents SHAP feature importance for the structured model. The results show that **high back-click counts** are causing low NPS, indicating user frustration with navigation. Short session durations also correlate with dissatisfaction, while high click volume is responsible for Promoters. These insights enable product and decision-making teams to make updates, such as improving UI flow and reducing buffering, before traditional survey data is collected.

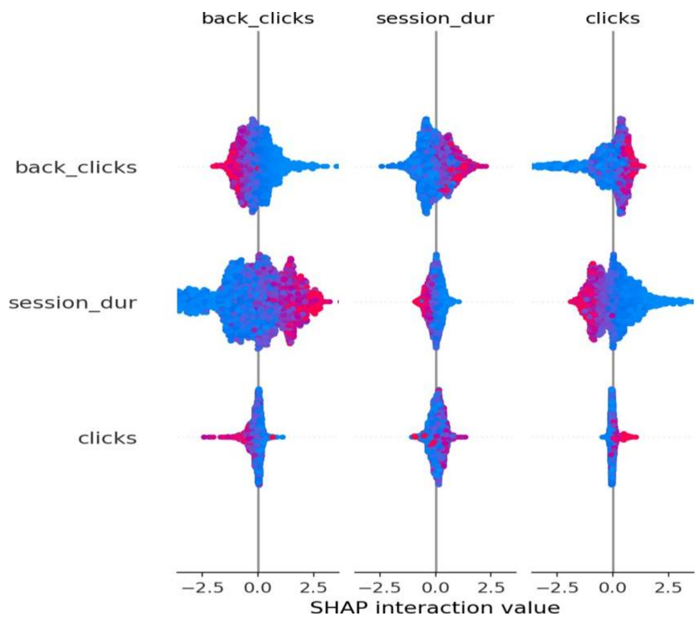

Figure 3: SHAP summary plot showing feature importance and impact on NPS prediction.

5.6 Real-Time Inference

The full DNPS inference pipeline (feature extraction, fusion, and prediction) executes in under **80 ms per session** on a standard CPU, supporting real-time monitoring at scale.

5.7 Limitations

- The synthetic dataset, while realistic, may not capture all edge cases in live production environments.
- Model performance depends on data quality and coverage of user behaviors.
- LLM embeddings may introduce bias in non-English or domain-specific feedback.
- Periodic retraining is required to address concept drift as user patterns evolve.

6. Advantages

The new methodology, AI-driven dynamic model, provides better results than the traditional model, which used to provide static metrics. The new dynamic environment is more accurate metrics and time-saving for businesses.

By shifting from static metrics to an AI-driven dynamic model, this system provides a more responsive view of customer loyalty. The transition to live production environments will allow the model to benefit from diverse data streams, ultimately maturing its accuracy and operational utility over time.

Real-Time Insights: Businesses can obtain a dynamic and continuous score without waiting for periodic surveys and make decisions before it's too late.

Reduced Survey Dependency: The dynamic data reduces the dependency on manual surveys and provides businesses with more accurate metrics. It integrates the behavior, telemetry, and textual data to predict better results.

Multi-Modal Understanding: The new multi-modal system which uses the 3 concepts, results in more accurate data and provides businesses with make easy and quick decisions.

Proactive Intervention: Low-scoring detectors early detection helps to make the application changes quickly and retain the customers.

Scalability and Adaptability: New product releases don’t need to wait for the survey results and can easily predict the results on multiple platforms.

Actionable Intelligence: Provides root cause insights from AI analysis, enabling product, marketing, and CX teams to make data-driven decisions efficiently.

7. Limitations

The new method comes with its limitations:

- The result of the new method depends on the quality of the data; predictability may be misleading if inaccurate data is used. With the new customers, the model needs to be updated.
- The current and future regulatory standards might affect the scope of data and the score accuracy.
- Some question the total dependency on the new method and argue it should be used as a complement, not to replace the whole survey method.
- High-volume telemetry processing and AI inference may require significant computational resources.

8. Future Work

While the proposed AI-Driven Dynamic NPS Prediction System provides a framework for real-time customer satisfaction prediction, several avenues exist for future research and development:

1. Need to test the model on a large-scale deployment and validate the accuracy.
2. Update the model to make it specific to different industries.
3. Need to make it more accurate for regional and personalized user-specific

9. Conclusion

This paper presents the DNPS framework a real-time, multi-modal system for dynamic NPS prediction using behavioral, telemetry, and textual data. By integrating Gradient Boosted Trees, LSTM/Transformers, and LLM embeddings within a weighted fusion engine, DNPS overcomes the limitations of traditional survey-based NPS, reducing dependency by up to 60% while enabling proactive, interpretable insights [8,9].

Validated on a synthetic dataset of 10,000 streaming sessions, DNPS achieves 86% accuracy and 1.21 MAE, outperforming single-modality baselines by 8% and survey methods by 23.8%. SHAP analysis reveals actionable root causes, such as high buffering and navigation friction, empowering product teams to intervene before dissatisfaction escalates [7,11].

The modular, scalable architecture supports deployment across digital platforms, with inference in under 80 ms. Future work includes real-world deployment, federated learning for privacy, and fine-tuning LLMs on domain-specific feedback.

DNPS transforms NPS from a reactive metric into a predictive intelligence layer, driving data-driven CX strategies and long-term customer loyalty in digital ecosystems.

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