Horizon.AI: Next Best Actions

LLM-driven tool for business (B2B) and customer (B2C) feedback analysis and satisfaction assessment

(Patent Pending)

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I Summary

Delivering exceptional customer experiences requires more than just collecting feedback: it demands actionable insights and seamless execution. Traditional feedback management tools provide valuable data but often do not drive timely and effective solutions, leading to higher churn rates and lower retention. Companies with high churn rates struggle to grow, as they must replace lost customers just to break even [1]. In short, churn and retention are critical metrics for any subscription or recurring revenue business because they directly affect revenue, customer lifetime value, and overall profitability.

Horizon.AI, powered by advanced AI and Large Language Models (LLMs), is a game changer. By automating feedback analysis and integrating insights across teams, this tool enables organizations to identify root causes, assign tasks with clarity, and act with speed and precision.

This innovation not only solves customer pain points efficiently, but also creates a proactive feedback loop that fosters trust and loyalty. With Horizon.AI, organizations can transition from passive feedback collection to a dynamic, action-driven approach, enhancing customer satisfaction, strengthening brand loyalty, and unlocking new growth opportunities.

AI-driven solutions have already shown significant impact: 69% of businesses report better consumer service, 55% experience reduced waiting times, and 54% achieve streamlined workflows after adopting AI technologies [2].

This white paper explores the limitations of current customer feedback systems and demonstrates how Horizon.AI transforms these challenges into opportunities for delivering superior customer satisfaction and business growth, boosting retention, and ultimately increasing customer lifetime value.

II Introduction

Service and product companies are typically founded with a mission: improving the lives of the people they serve. However, achieving this mission critically depends on another factor: customer satisfaction (CSAT) with the services and products provided. CSAT reflects the effectiveness of the offerings and highlights areas for improvement to ensure that consumers receive experiences tailored to their expectations. To understand consumer viewpoints, organizations often rely on tools such as Qualtrics, Medallia, and customer interviews to curate CSAT trends and insights. These tools offer qualitative comment analysis by identifying top concerns and recurring keywords. While this is valuable, a significant gap exists in transforming these insights into actionable solutions and ensuring they are implemented quickly and effectively. For instance, if customers of a phone brand report that "battery life is bad," identifying who needs to take action and ensuring timely resolution remains a challenge. This is because:

1) **Data silos:** Customer feedback data is often fragmented across departments (e.g., customer service, product development, marketing), making it difficult to get a holistic view of customer sentiment and identify root causes.
2) **Lack of clear ownership**: Ambiguity around responsibility for addressing specific concerns leads to delays and miscommunication, hindering timely resolution.
3) **Limited automation**: Many companies still rely on manual processes to analyze customer feedback and assign tasks, which is time-consuming and prone to errors.

4) **Lack of integration:** Customer feedback is often not integrated with other relevant data sources, such as product usage or social media sentiment, limiting its value and actionable insights.

These challenges are significant, considering that 73% of consumers will switch to a competitor after multiple bad experiences, and more than half will leave after just one negative experience. [3] Beyond these statistics, businesses are also seeing an overall increase in customer retention and loyalty due to AI-driven engagement. According to industry reports, 58% of customers say that AI-based customer service solutions have improved their overall experience [4], leading to stronger brand trust and repeat business. These metrics highlight a growing need for AI-driven feedback solutions that go beyond traditional data collection and actively drive improvements.

II.A The Core Problem: Improving Customer Retention and Reducing Churn Rates

Organizations struggle to bridge the gap between gathering feedback and taking meaningful actions to reduce customer churn. This white paper explores how AI-powered solutions like Horizon.AI can revolutionize customer satisfaction, retention, and business growth. Despite knowing the importance of retention, many businesses today struggle with high churn rates**,** which erode their customer base and revenue. A high churn rate often signals that customers are unhappy with the product or service, making churn both a financial and a customer satisfaction problem. To make matters worse, when those customers leave, the company loses not only the ongoing revenue but also the investment made to acquire them in the first place. Replacing lost customers is expensive: acquiring a new customer can cost 5 to 25 times more than keeping an existing one [5]. In other words, churn directly translates to revenue loss and higher costs, creating a double hit to business performance.

II.B Defining Customer Retention and Churn Rate

Customer churn rate is the percentage of customers who leave (cancel or stop using a service) during a given period [6].Conversely, the retention rate measures the percentage of customers a company keeps in that period, expressed as: Customer Retention Rate = 100% - Churn Rate. Churn is more than just a number – it's directly tied to revenue and is a telling indicator of customer satisfaction. A high churn rate means a business is losing customers faster than it's gaining them, which significantly impacts revenues and profits [7].In contrast, strong customer retention drives sustainable growth and profitability.

To quantify these concepts, companies track key metrics and formulas. For example, churn rate (CR) can be calculated as:

$$CR = \frac{\text{Customers lost during a period}}{\text{Total customers at start of period}} \times 100\% \tag{1}$$

meaning if you had 1,000 customers in January 2024, and only had 950 customers by March 2024, your churn rate is 5%, and the customer retention rate would be 95% (100% – CR). High retention is obviously desirable: a retention rate of 100% (zero churn) is the ideal, though rarely achievable. Another vital metric is Customer Lifetime Value (CLV) – the total revenue a business expects to earn from a customer over the life of the relationship and provides insights into viability of the product and business model. One common formula for CLV is:

$$CLV = \frac{\text{Average Revenue per User (ARPU)} \times \text{Gross Margin \%}}{\text{Churn Rate}} \tag{2}$$

where:

- ARPU**:** The average revenue per year for a customer over a given time period (e.g., one year).
- Gross Margin**:** $\frac{\text{Revenue} - \text{Cost of Goods Sold (COGS)}}{\text{Revenue}} \times 100\%$

CLV is inversely proportional to churn rate. Lower churn (higher retention) leads to a longer customer 'lifespan' or loyalty, which increases the revenue a customer generates over time. In other words, if churn rises, CLV falls- meaning customers don't stay long enough. It's important to note that the formulas provided above simplifies the relation of CLV and churn rates. In reality, multiple factors influence customer lifetime value, and all these metrics must be considered holistically to determine the true value of a customer's lifespan.

III Problem Statement

Many organizations still struggle to convert customer feedback into measurable improvements and focus on customer retention. Companies that fail to address churn risk stagnation and revenue loss.

IV Proposed Solution

AI-driven solutions like Horizon.AI bridge the gap between gathering feedback and implementing actionable changes, ensuring a seamless, proactive approach to customer satisfaction. By leveraging AI and LLMs, businesses can uncover deeper customer insights, anticipate needs, and deliver personalized experiences that drive engagement and satisfaction, Horizon.AI transforms customer feedback from a passive data source into a strategic advantage—reducing churn, increasing CLV, and driving long-term business success.

It's well established that retaining customers is far more cost-effective and lucrative than constantly acquiring new ones. Companies with high churn rates struggle to grow, as they must replace lost customers just to break even. For example, the UK retailer Travis Perkins applied an AI-driven churn prediction model and was able to reduce customer churn by 54%. As more customers stayed on board, the customer lifetime value jumped by 34% in just one year for the business [8]. This case highlights how AI and machine learning can directly increase CLV by saving more customers from leaving.

By leveraging predictive models to keep customers happy and engaged, companies not only *stop the bleeding* of revenue loss but strengthen customer relationships, leading to longer lifetimes and higher value per customer.

Horizon.AI is fueled by the same motivation. By automating feedback analysis, this tool ensures that insights lead to measurable actions, which improve member experiences and increase customer retention rates. It ensures seamless data aggregation across sources (Cloud, CRM, social media, etc.), automated categorization using transformer-based NLP models, LLM-powered recommendations for next-best actions and workflow automation with integrations to tools like JIRA, ServiceNow, and Asana.

This MVP of Horizon.AI is designed to enhance efficiency in customer feedback analysis by leveraging AI-driven automation. The MVP of Horizon.AI is designed to provide a robust and scalable solution for gathering, analyzing, and acting on continuous feedback from various sources.

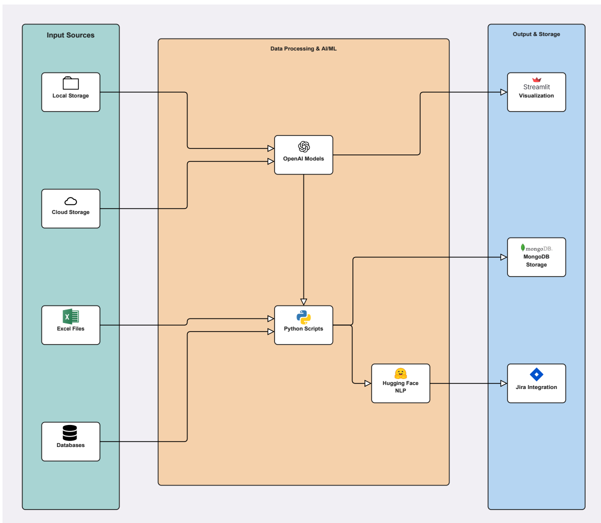

Fig. 1 *System Architecture of Horizon.AI: The architecture consists of a multi-cloud ingestion layer, a transformer-based categorization engine, an LLM-powered task assignment module, and an interactive analytics dashboard.*

The tool leverages state-of-the-art AI and machine learning techniques to automate key processes and provide actionable insights.

1) **Multi-Cloud Ingestion Layer:** This layer facilitates seamless data ingestion from diverse sources, including public and private clouds (AWS, Azure, GCP), and on-premises systems. Data is standardized and stored in a centralized data lake for further processing. In future iterations, Apache Kafka will be leveraged to handle

the high throughput data streaming from these various sources, ensuring real-time availability for downstream processing.

2) **LLM-Powered Task Assignment Module:** Incoming feedback is analyzed and categorized using fine-tuned transformer models, specifically a variant of BERT fine-tuned on a curated dataset of thousand customer feedback entries to build a proprietary model that achieves optimal accuracy in sentiment classification and topic extraction. The model assigns tasks based on the nature of the feedback (e.g., bug reports, feature requests, customer service inquiries) and routes them to the appropriate teams. We employ a hierarchical classification approach, where the model first identifies the broad feedback category and then further refines it into specific subcategories.
3) **Automated Feedback Clustering & Summarization:** Similar feedback items are grouped using a combination of BERTopic and KMeans clustering. BERTopic, a topic modeling technique based on transformer embeddings, identifies semantically similar feedback clusters. KMeans clustering further refines these clusters based on specific keywords and phrases. This approach ensures that feedback with similar underlying themes is grouped, even if expressed differently. The system then generates concise summaries for each cluster using Horizon. AI's proprietary model(to protect IP rights, the formula and exact techniques cannot be disclosed) highlights key themes and sentiment trends. GPT-4 models are then leveraged to recommend the next best actions for the categorized data.
4) **Multi-Source Feedback Aggregation:** Feedback from various sources is aggregated and analyzed holistically. The system identifies correlations and patterns across channels, providing a comprehensive view of customer sentiment and feedback trends. For example, the negative sentiment expressed on social media regarding a specific feature can be correlated with increased support tickets related to the same feature, providing valuable insights for product development and customer service teams.
5) **Multi-Source Feedback Aggregation:** Feedback from various sources is aggregated and analyzed holistically. The system identifies correlations and patterns across channels, providing a comprehensive view of customer sentiment and feedback trends. For example, the negative sentiment expressed on social media regarding a specific feature can be correlated with increased support tickets related to the same feature, providing valuable insights for product development and customer service teams.
6) **Actionable Insights & Reporting:** Horizon.AI provides actionable insights through interactive dashboards and reports. These reports highlight key trends, areas of concern, and opportunities for improvement. Based on the analysis, the system also provides recommendations for action, such as prioritizing bug fixes, addressing customer service issues, or developing new features.

IV.A What powers Horizon.AI?

At its core, Horizon.AI is built on advanced natural language processing (NLP) techniques that enable dynamic text categorization. Traditional classification models rely on predefined taxonomies or supervised learning with extensive labeled datasets. However, real-world feedback is highly dynamic, requiring adaptive categorization methods that can identify and respond to emerging topics in real time.

Horizon.AI bridges this gap by combining statistical frequency analysis, semantic embeddings, and adaptive clustering techniques to create a system that is both scalable and intelligent. By continuously learning from new data, it evolves alongside user feedback, ensuring more accurate categorization and actionable insights over time.

IV.B Let's understand the mathematics behind Horizon.AI's Intelligence

A core aspect of this approach is the use of word frequency distributions to identify emerging terms. Given a corpus D, we define the occurrence count of a word as:

$$f(w) = \sum_{d_i \in D} 1(w \in d_i)$$

where

$$1(w \in d_i) = \begin{cases} 1, & \text{if word } w \text{ appears in document } d_i \\ 0, & \text{otherwise} \end{cases}$$

To determine statistical significance, we define an adaptive cutoff T, which is derived from the distribution of term occurrences. The threshold is computed using a combination of the interquartile range (IQR) and percentile-based heuristics:

$$T = \max(A + k \cdot B, D)^{**}$$

where:

$$\begin{aligned} A &= \text{quartile-based metric from the distribution,} \\ k &= \text{scaling factor based on keywords,} \\ B &= \text{spread of data based on quartiles,} \\ D &= \text{percentile-based threshold} \end{aligned}$$

***(The exact formula has been withheld since it's a proprietary model undergoing IP protection.)*

This IQR-based thresholding forms the core of Horizon.AI's proprietary categorization model. By fine-tuning the parameters in these equations, we achieved approximately 70% accuracy in classifying customer comments. For example, the statement: "The camera quality is bad." would be automatically categorized under the "camera" category.

We can further refine the threshold T by computing the deviation score for each term:

$$z(w) = \frac{f(w) - \mu_F}{\sigma_F}$$

such that μ_F and σ_F represent the mean and standard deviation, respectively. Words exceeding a predefined deviation threshold are classified as high-impact terms and considered for further processing.

While frequency analysis provides a statistical backbone for keyword selection, it does not capture the underlying meaning of words. To enhance categorization, each word is mapped to a high-dimensional vector space using a function $\mathbb{E} : W \to \mathbb{R}^d$, where d is the embedding dimensionality. The semantic importance of a word is weighted as follows:

$$\varphi(w) = \alpha F(w) + \beta \|E(w)\|_2 + \gamma \frac{1}{1 + e^{-z(w)}}$$

where:

$$\begin{aligned} F(w)^{**} &= \text{frequency-based metric for statistical significance,} \\ \|E(w)\|_2 &= \text{L2 norm of embedding vector,} \\ \frac{1}{1 + e^{-z(w)}} &= \text{non-linear transformation,} \\ \alpha, \beta, \gamma &= \text{scaling factors} \end{aligned}$$

** ($F(w)$ is withheld as it's a proprietary model undergoing patent and IP protection.)

V Evaluation

The MVP of Horizon.AI achieved 70% accuracy in automatically classifying and routing feedback items when trained on a pre-classified dataset. The dataset was modified by removing the **'**Category**'** column, and model accuracy was evaluated based on the number of correctly assigned categories compared to the original labeled dataset.

V.A Benchmarking and Comparative Analysis

To validate Horizon.AI's performance, the model was benchmarked against:

1) **Traditional Keyword-Based Approaches:** The model outperformed rule-based keyword extraction techniques, which had an accuracy of approximately 55%, showing that the AI-based approach significantly reduces misclassifications due to synonym variations and context dependencies.
2) **Supervised Learning Baselines:** Comparisons with logistic regression and random forest classifiers showed that Horizon.AI's deep-learning-based categorization exhibited superior generalization capability.

3) **Human Performance:** A subset of feedback items was manually classified by domain experts to establish an upper-bound baseline. The AI model currently achieves near-human performance for certain categories, but there remains an accuracy gap in subjective categories (e.g., sentiment-driven feedback).

V.B Improvement Opportunities

While the initial results are promising, several areas for improvement have been identified:

1) **Active Learning:** Implement active learning to continuously improve the accuracy of the models by selectively querying human experts for labels on ambiguous or challenging feedback items.
2) **Semi-supervised Clustering:** Utilize semi-supervised clustering techniques to leverage existing labeled data to improve the accuracy of feedback clustering.
3) **Reinforcement Learning:** Explore the use of reinforcement learning to optimize task assignment and routing based on feedback outcomes and user satisfaction.
4) **Explainable AI (XAI):** Integrate XAI techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to provide transparency into the AI's decision-making process and build trust with users.

By advancing these capabilities, Horizon.AI aims to move beyond efficiency improvements and establish itself as an AI-powered consumer feedback analytics platform that automates feedback analysis and drives strategic decision-making. Future iterations will incorporate active learning, reinforcement learning, and hybrid human-in-the-loop systems to improve accuracy and reliability further.

VI Case Studies

Horizon.AI is actively under development, and a pilot study to test its accuracy is still pending. However, its impact on businesses—ranging from cost reduction to addressing customer churn—can be further analyzed through the following hypothetical scenarios based on synthetic data.

VI.A Example Study #1: Xiaomi Redmi Phone – Kaggle Dataset

Redmi, a sub-brand of Xiaomi, is known for its affordable smartphones with high-end features. However, Redmi faces a major challenge: customer churn due to unresolved product issues like poor camera quality, battery drainage, and software bugs. While Redmi collects feedback from various channels (social media, forums, support tickets, and e-commerce reviews), its existing system struggles to quickly categorize and address critical concerns, leading to customer frustration and potential churn.

To tackle this, Horizon.AI was deployed to automate feedback analysis, detect emerging trends, and prioritize fixes that could reduce churn and enhance customer satisfaction.

VI.A.1 Challenges Faced by Redmi

1) **High Volume of Customer Reviews:** Thousands of reviews pour in daily, making manual processing slow.
2) **Inconsistent Issue Categorization:** Complaints about the same issue (e.g., "bad camera," "blurry photos," "low light issues") were scattered, leading to delayed insights.
3) **Longer Issue Resolution Times:** Without proper categorization, the product team struggled to identify high-priority fixes.
4) **Customer Churn Due to Unresolved Issues:** Delayed responses to complaints led users to switch competitors.

VI.A.2 How Horizon.AI Transformed Redmi's Feedback Analysis

1) Automating Feedback Aggregation & Categorization
Horizon.AI ingested feedback from numerous sources, analyzing thousands of reviews in real-time. By leveraging AI-powered clustering, similar complaints were grouped automatically, reducing processing times.

Examples:

- "The camera is terrible in low light."
- "Selfies come out grainy at night."

- "Blurry photos in dim rooms."

These were mapped under Camera using Horizon.AI's NLP mechanism.

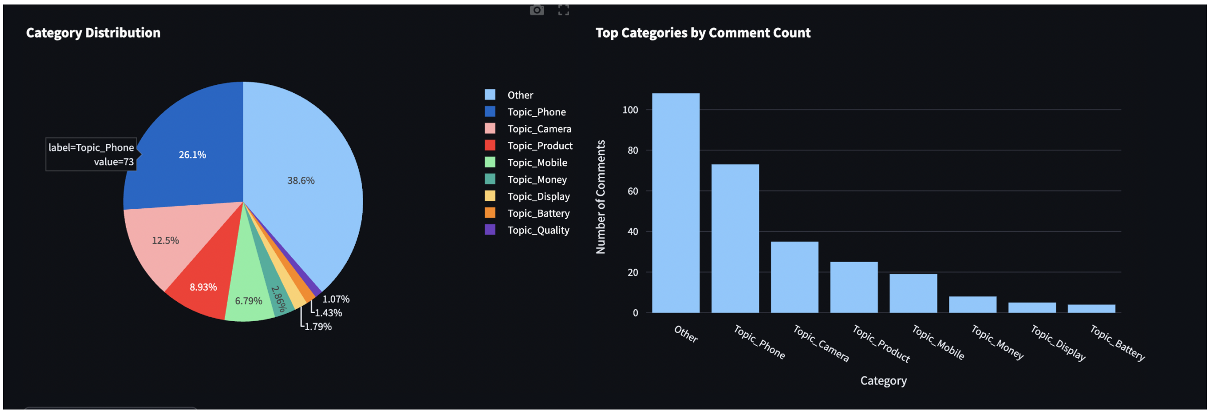

Fig. 2 *Horizon.AI in action: Categories generated at 70% accuracy through statistical and AI based models*

2) Identifying Root Causes & Emerging Trends
Horizon.AI applied adaptive thresholding to detect which complaints were statistically significant.

Example: "Fingerprint sensor not working" complaints increased in a specific device model. This feedback was directly sent to engineering for investigation.

3) Automating Issue Resolution & Customer Support Workflows
By integrating with JIRA & Xiaomi's internal ticketing system, Horizon.AI automatically assigned & tracked issues, reducing resolution times signifcantly.

4) Predicting Customer Churn & Taking Proactive Action
Horizon.AI used predictive modeling to correlate review sentiment with purchase behavior, returns, and competitor brand switches. The tool predicted high-risk churn users, allowing Xiaomi to proactively offer solutions.

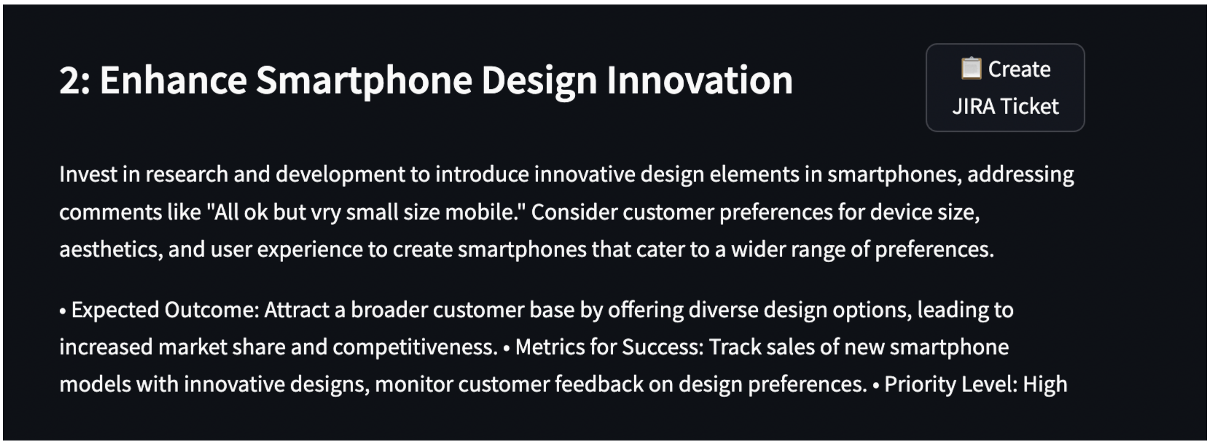

Fig. 3 *Horizon.AI in action: LLM Model helps identify emerging trends. The Create JIRA Ticket button automatically generates a ticket which can be tracked for issue resolution*

Before implementing Horizon.AI, analyzing 300 customer reviews manually required approximately 10 hours, assuming an average processing time of 2 minutes per review. With AI-powered automation, the same volume is processed in just 2.5 minutes, representing a 99.6% reduction in effort.

$$\text{Time Saved} = \left(\frac{600 - 2.5}{600}\right) \times 100 \approx 99.6\% \tag{3}$$

This substantial reduction allowed Xiaomi's product team to focus on strategic decision-making and high-impact fixes, rather than manual review processing. The faster insights enabled quicker resolutions, reducing customer churn and enhancing overall satisfaction.

VI.B Example Study #2: HeartHealth – Health Insurance Company (Hypothetical Scenario)

HeartHealth, a large multinational health insurance company, receives thousands of consumer reviews and complaints daily across multiple channels—email, live chat, calls, etc. Common complaints include: terrible UI, poor customer service experience, and confusion regarding health plans.

VI.B.1 Challenges Faced by HeartHealth

While HeartHealth stored feedback using tools like Qualtrics and Medallia, their existing feedback analysis process relied on manual issue classification, leading to delays in improving the member experience. This resulted in longer resolution times and lower satisfaction rates.

VI.B.2 How Horizon.AI Helped HeartHealth

Horizon.AI ingested and categorized feedback from all sources in real-time. The LLM-powered clustering engine grouped complaints related to "poor customer service" and revealed that customer reps needed additional training. Horizon.AI routed feedback to the logistics team and integrated directly with JIRA, triggering automated resolution workflows.

Key Impact of Horizon.AI on HeartHealth:

1) Customer response times improved by 40%(hypothetical improvement)
2) Net Promoter Scores (NPS) increased by 10%.(hypothetical improvement)
3) Estimated cost savings of $500K annually due to reduced manual feedback processing(hypothetical cost savings)

VII Comparative Analysis of Horizon.AI and CSAT Tools

Feature	**Qualtrics**	**Medallia**	**Zendesk**	**Horizon.AI**
AI-Powered Feedback Categorization	No	No	No	Yes
LLM-Powered Summarization & Recommendations	No	No	No	Yes
Automated Task Assignment	No	Yes	No	Yes
Feedback Clustering for Deep Insights	Yes	Yes	No	Yes
Dashboarding and Real-Time Report Generation	Yes	Yes	Yes	Yes
Context-Aware Sentiment Analysis	Yes	Yes	Yes	Yes

Table 1 ***Comparison of Horizon.AI against existing CSAT tools that collect and analyze feedback. While some platforms include NLP and automated categorization, they may lack the robust framework that Horizon.AI provides. Further research is advised, as existing platforms may introduce advancements over time. Data sources: [9], [10], [11].***

VIII Future Vision and Next Steps

Horizon.AI represents a significant step toward transforming customer feedback into actionable intelligence, but its potential extends far beyond its current capabilities. As AI and LLM-driven automation continues to evolve, future iterations of Horizon.AI will focus on expanding its impact in several key areas:

1) **Adaptive Learning & Continuous Improvement:** Horizon.AI will integrate active learning mechanisms, allowing models to continuously refine their accuracy by incorporating user corrections and expert feedback. Future updates will enable unsupervised and semi-supervised learning, ensuring that the tool adapts dynamically to new feedback trends without requiring constant manual intervention.

2) **Cross-Platform & Multimodal Feedback Integration:** Expanding beyond text-based analysis, Horizon.AI will incorporate voice, video, and image-based feedback, using multimodal AI techniques to extract insights from sources such as call center transcripts and social media images. Advanced integrations with IoT and smart assistants could allow businesses to capture real-time customer sentiment across various touchpoints.
3) **Personalized Customer Engagement & Chatbots:** Future updates will include seamless integration with LLM-powered conversational agents that provide immediate, AI-driven responses to customer concerns. Businesses can configure automated responses based on sentiment, intent, and urgency, ensuring a more personalized and proactive engagement strategy.
4) **Regulatory Compliance & Ethical AI:** Future versions will incorporate explainable AI (XAI) techniques to ensure transparency in decision-making and build user trust. To support industries with strict compliance requirements (e.g., healthcare and finance), Horizon.AI will introduce features to align with GDPR, HIPAA, and CCPA while maintaining high data security and privacy standards.
5) **Ecosystem Expansion & Integrations:** Horizon.AI aims to expand its API ecosystem, allowing integrations with a broader range of enterprise software, such as ERP systems, customer data platforms (CDPs), and CRM solutions. Collaborations with third-party AI and ML providers will further enhance its analytical depth and automation capabilities.

With these advancements, Horizon.AI is poised to become a feedback analysis tool and a comprehensive AI-driven customer experience management platform. The goal is to evolve from a system that identifies issues to one that actively prevents them, enabling businesses to engage with customers at a deeper, more personalized level.

IX Conclusion

The ability to gather customer feedback is no longer a competitive advantage—it is an expectation. A business is ability to act on that feedback efficiently and intelligently differentiates it. Traditional feedback analysis methods, while helpful, often fall short of turning insights into action due to data silos, limited automation, and slow execution cycles.

Horizon.AI bridges this gap by automating, categorizing, and integrating feedback insights directly into business workflows. This ensures that organizations can respond to concerns with speed, precision, and strategic intent. Its LLM-powered task assignment, advanced clustering, and actionable insights enable teams to transition from passive problem-solving to proactive engagement, ultimately driving stronger customer satisfaction and brand loyalty.

By harnessing the power of AI, organizations that implement Horizon.AI will not only solve problems faster but also anticipate them before they arise, reinforcing a customer-centric culture that drives long-term success.

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