

Trustpilot Review Analysis

Key Insights

Objective

Understand **why customers are dissatisfied**
and whether issues are **one-off or recurring**.

What Was Done:

- Cleaned and normalized review text
- Built a **pet-product–specific sentiment dictionary**
- Classified reviews by **sentiment** and **complaint theme**
- Identified **repeat reviewers** using cleaned customer names

Key Findings

Customer Support Is the Top Complaint

Most negative reviews relate to **unresponsive or unresolved support**.

More frequent than food safety, shipping, or pricing issues.

Food Safety Issues Are Less Frequent but High Severity

Complaints about **rancid or expired food** appear less often.

But pose **significant trust and brand risk**.

Most Negative Reviews Are One-Time Events

84.5% of negative reviews come from **one-time reviewers**.

Suggests many issues are isolated or situational.

Repeat Reviewers Signal Unresolved Problems

15.5% of negative reviews come from **repeat customers**.

These reviews cluster around **customer support failures**.

Business Implication

Improving **first-response customer support** would likely reduce the largest share of negative sentiment and prevent repeat complaints.

Visualizations

Top Complaint Themes from Negative Reviews



What this chart shows

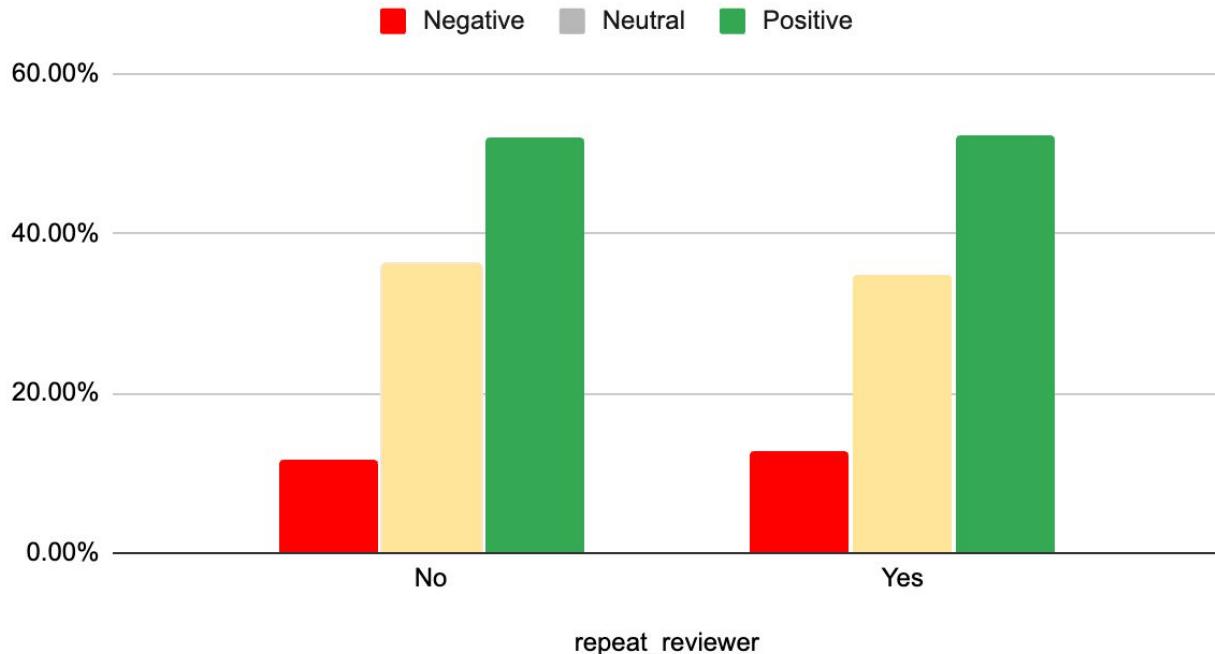
This chart breaks down **negative customer reviews** by the main reason for dissatisfaction, such as customer support, food safety, or shipping issues.

Why it matters

It highlights **where problems occur most often**.

The largest bars show the issues that create the most frustration and should be prioritized for improvement.

Sentiment by Reviewer Type (Repeat vs One-Time)



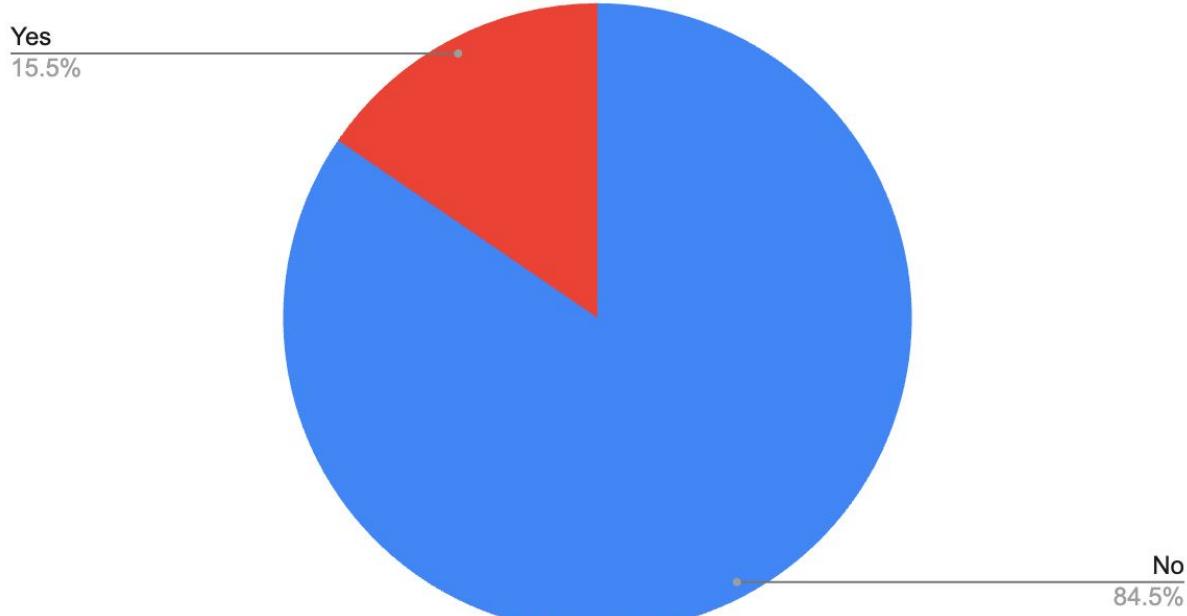
What this chart shows

This chart compares **one-time reviewers** and **repeat reviewers** to see whether customers who write multiple reviews are more likely to be negative.

Why it matters

It helps identify whether negative sentiment comes from **isolated incidents** or from customers experiencing **ongoing unresolved problems**.

Repeating users on negative comments



What this chart shows

This chart shows **what portion of negative reviews** come from customers who have written more than one review.

Why it matters

It reveals whether negative feedback is driven by a **small group of repeat complainers** or by many different customers.

In this case, most negative reviews come from one-time reviewers, with a smaller but important group of repeat customers signaling unresolved issues.

Follow up actions

First-Response Customer Support (Highest Impact)

Business action

- Set **response-time targets** for first contact
- Add visibility so customers know **their issue is being handled**
- Improve follow-up consistency (no silent drop-offs)

Faster and clearer support would likely prevent many one-time complaints and reduce repeat negative reviews.

Treat Food Safety Issues as High-Severity Alerts

Business action

- Flag food quality complaints for **immediate escalation**
- Audit suppliers or storage processes tied to these complaints
- Proactively reach out to affected customers

Even a small number of food safety complaints can damage long-term trust and brand reputation.

Use Repeat Reviewers as an Early Warning System

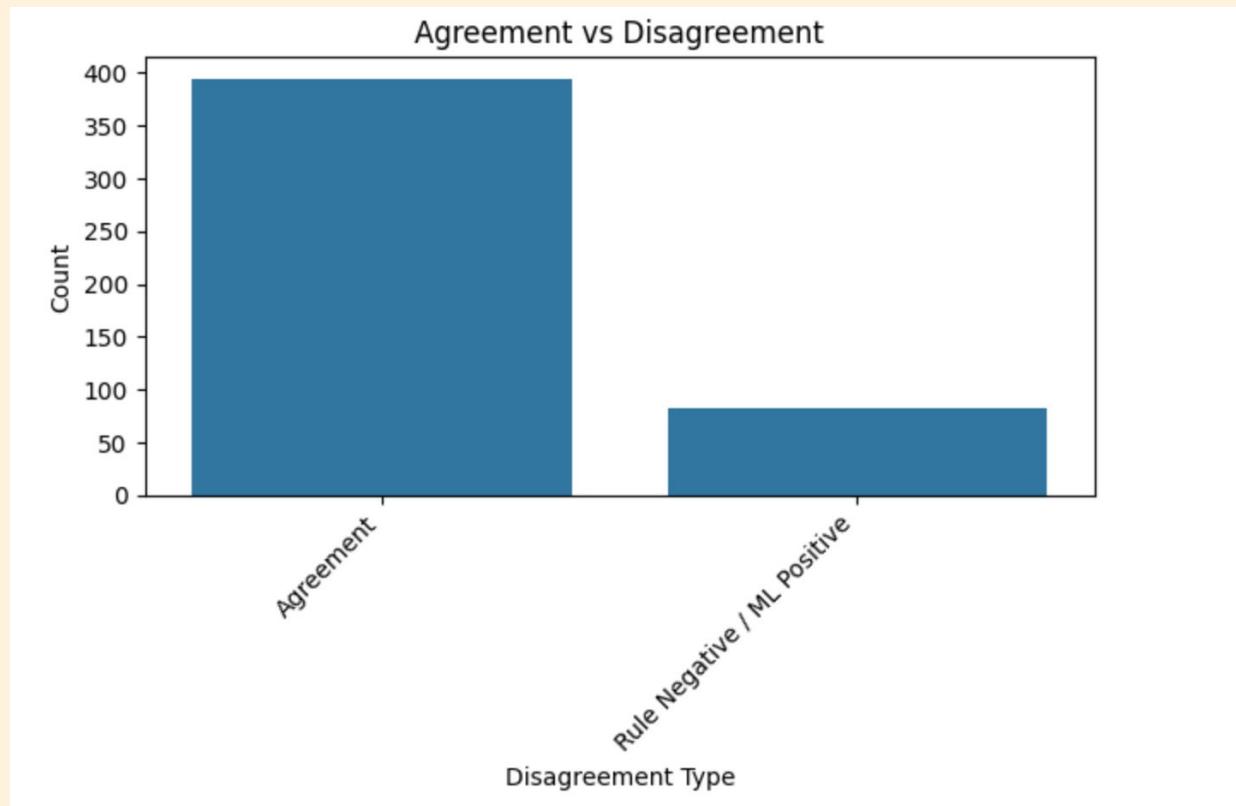
Business action

- Track repeat complainants internally
- Prioritize resolution for customers who contact support more than once
- Use repeat complaints to identify **process gaps**

Repeat reviewers represent a small but important group that signals systemic issues before they escalate.

Machine Learning

Model: Naïve Bayes



Key Results

High Overall Agreement

- The ML model agrees with rule-based sentiment in **most cases**
- Indicates the model successfully learned common sentiment patterns

Meaningful Disagreements

- Disagreements occur mainly in:
 - Reviews with **mixed sentiment**
 - **Service recovery** cases (initial issue, positive resolution)
- These reviews require **context**, not just keywords

Key Takeaway

Machine learning confirms overall sentiment trends, while disagreements highlight complex customer experiences that benefit from human or rule-based interpretation.

After using the Naïve Bayes model to see whether machine learning could learn sentiment patterns from review text it was found that the model performs well overall, but disagreements highlight complex reviews where context matters more than individual words.

This shows why combining rule-based logic with machine learning leads to more reliable insights.

Conclusion

This analysis shows how customer feedback can be turned into action.

By grouping complaints and identifying repeat behavior, we uncovered where dissatisfaction truly comes from.

Better customer support would reduce the majority of negative reviews, while rapid response to food safety issues would protect long-term trust.

The Naïve Bayes model helped to validate sentiment patterns and identify complex reviews where context matters.