

Youtube Comment Behaviour Analysis Report

Prepared By Soniya

Client / Stakeholder : Youtube

Purpose :

This project will analyze the Youtube Comments behaviour dataset to detect negative sentiment, engagement patterns, and potential abuse trends — insights that help shape content moderation and policy enforcement.

Summary :

This analysis explores over 1 million YouTube comments across 4,563 videos, focusing on sentiment distribution, user behavior, engagement trends, and negativity patterns to support Trust & Safety decisions. Results show balanced sentiment distribution (~33% each), with Shorts and emotionally charged videos driving the highest comment volume. Several videos show >85% negative sentiment and require moderation attention. A suspicious high-volume user posted 150K+ comments with 68% negativity, suggesting automated or abusive behavior. Country-level analysis reveals PH, IE, and GB with highest negativity rates. Time trends indicate sentiment spikes across years, highlighting the need for continuous moderation.

Phase I - Ask :

- Identified Business task
- Considered key Stakeholders
- BrainStormed SMART questions

❖ **Business Task :**

- Analyze YouTube comment data to identify trends in user engagement, sentiment polarity, and potential abusive patterns across videos, channels, and categories — to support proactive Trust & Safety enforcement decisions.

❖ **Stakeholder:**

- Mr. Y (Marketing Director)

*Note: SMART questions sheet is attached separately

Phase II - Prepare :

- The dataset includes Youtube Comments data from Huggingface.
- Each record represents a comment with details such as Comment id, Video Id, Video Title, Author Name, Author Channel Id, Comment Text, Sentiment, Likes, Replies, Published At, Country Code, Category Id.
- Open Source data is used here from trustable sources.
- The dataset is relevant, credible, and historical data.
- Columns used for analysis are Video Title, Author Name, Comment Text, Sentiment, Likes, Replies, Published At, Country Code.

Phase III - Process :

```
CREATE OR REPLACE TABLE
`data-analysis-youtube-comment.youtube_comment.youtube_comments` AS
SELECT
-- remove exact duplicates
DISTINCT *
FROM (
SELECT
| CommentId,
VideoId,
VideoTitle,
AuthorName,
AuthorChannelId,
-- Clean comment text
REGEXP_REPLACE(TRIM(CommentText), r'\s+', ' ') AS CommentText,
-- Standardize sentiment values
CASE
WHEN LOWER(Sentiment) LIKE '%pos%' THEN 'Positive'
WHEN LOWER(Sentiment) LIKE '%neg%' THEN 'Negative'
WHEN LOWER(Sentiment) LIKE '%neu%' THEN 'Neutral'
ELSE Sentiment
END AS Sentiment,
-- Convert likes + replies to safe integers
SAFE_CAST(Likes AS INT64) AS Likes,
SAFE_CAST(Replies AS INT64) AS Replies,
-- Convert timestamp
TIMESTAMP(PublishedAt) AS PublishedAt,
CountryCode,
CategoryId
FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
WHERE CommentText IS NOT NULL
| AND TRIM(CommentText) <> '' -- remove empty comments
);
```

Fig 1. Cleaning - i

```
CREATE OR REPLACE TABLE
`data-analysis-youtube-comment.youtube_comment.youtube_comments` AS
SELECT
|,
DATE(PublishedAt) AS DatePosted,
FORMAT_DATE('%Y-%m', DATE(PublishedAt)) AS MonthPosted,
EXTRACT(YEAR FROM PublishedAt) AS YearPosted
FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`;
```

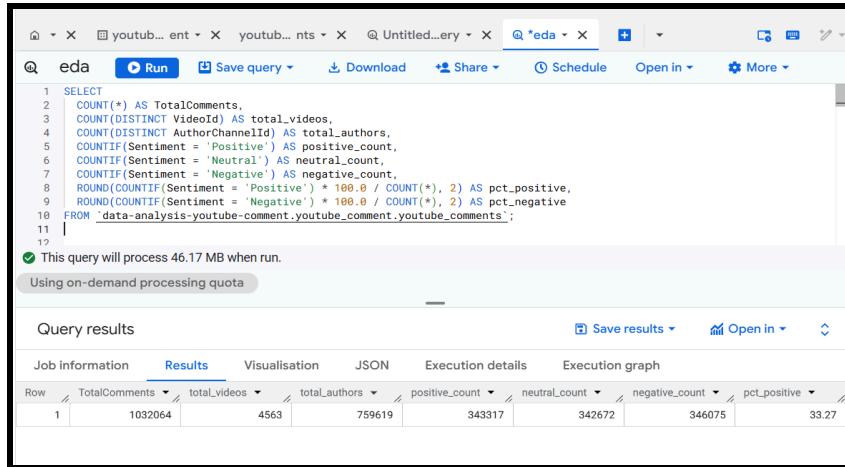
Fig 2. Creating month and year from Published At

- **Tool Used :** BigQuery, SQL
- Ensured Data Integrity.
- Removed null or blank values in **CommentId**, **CommentText**, **Sentiment**, **Likes** and **PublishedAt**.
- Removed Duplicate records in **CommentId** and trim whitespaces in **CommentText**.
- Standardized Sentiment Values as **Positive**, **Negative**, **Neutral**.
- Convert **Likes** and **Replies** columns to safe integers.
- Extracted **Month** and **Year** from **PublishedAt**.
- Verified data types and formatting for consistency.
- The data is cleaned, organized and well maintained.
- The dataset contains usernames both with and without the "@" prefix. This is expected because YouTube introduced @handles in 2022, while older accounts still use display names. Some usernames (AugmentedUser) may also appear system-generated or bot-like, which reflects real user behavior and enhances moderation analysis. This does not affect data quality or skew the results.

Phase IV - Analyse :

❖ Figure 1:

- This query displays total number of comments, videos, authors, positive comment count, negative count comment, negative comment percentage and positive comment percentage.



The screenshot shows a data analysis interface with a query editor and a results table. The query editor contains the following SQL code:

```
1 SELECT
2     COUNT(*) AS TotalComments,
3     COUNT(DISTINCT VideoId) AS total_videos,
4     COUNT(DISTINCT AuthorChannelId) AS total_authors,
5     COUNTIF(Sentiment = 'Positive') AS positive_count,
6     COUNTIF(Sentiment = 'Neutral') AS neutral_count,
7     COUNTIF(Sentiment = 'Negative') AS negative_count,
8     ROUND(COUNTIF(Sentiment = 'Positive') * 100.0 / COUNT(*), 2) AS pct_positive,
9     ROUND(COUNTIF(Sentiment = 'Negative') * 100.0 / COUNT(*), 2) AS pct_negative
10    FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`;
11
12
```

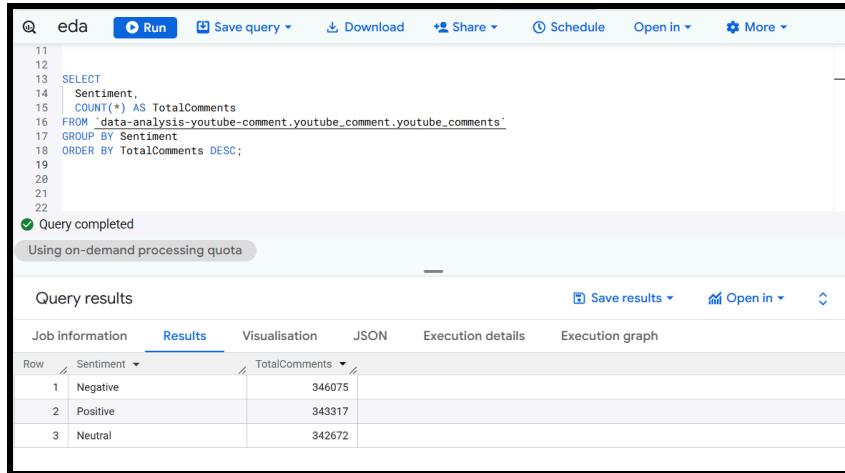
A note below the code says "This query will process 46.17 MB when run." The results table has columns: Row, TotalComments, total_videos, total_authors, positive_count, neutral_count, negative_count, pct_positive. The data row is:

Row	TotalComments	total_videos	total_authors	positive_count	neutral_count	negative_count	pct_positive
1	1032064	4563	759619	343317	342672	346075	33.27

Fig 1. Overall Dataset Summary

❖ Figure 2:

- This query displays a segregated count of Negative, Positive, Neutral from total comments.



The screenshot shows a data analysis interface with a query editor and a results table. The query editor contains the following SQL code:

```
11
12
13 SELECT
14     Sentiment,
15     COUNT(*) AS TotalComments
16    FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
17   GROUP BY Sentiment
18  ORDER BY TotalComments DESC;
19
20
21
22
```

A note below the code says "Query completed". The results table has columns: Row, Sentiment, TotalComments. The data rows are:

Row	Sentiment	TotalComments
1	Negative	346075
2	Positive	343317
3	Neutral	342672

Fig 2. Sentiment Distribution Summary

❖ Figure 3:

- This displays the Average Replies, Average Likes and Total Comments based on Sentiment.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
30 SELECT
31   Sentiment,
32   ROUND(AVG(Likes), 2) AS avg_likes,
33   ROUND(AVG(Replies), 2) AS avg_replies,
34   COUNT(*) AS TotalComments
35 FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
36 GROUP BY Sentiment
37 ORDER BY avg_likes DESC;
38
```

A green checkmark indicates "Query completed". Below the editor is a message: "Using on-demand processing quota".

The "Query results" section displays the following table:

Job information	Results	Visualisation	JSON	Execution details	Execution graph
Row	Sentiment	avg_likes	avg_replies	TotalComments	
1	Positive	148.56	2.34	343317	
2	Neutral	102.08	1.74	342672	
3	Negative	54.77	1.99	346075	

Fig 3. Average Likes & Replies by Sentiment

❖ Figure 4:

- This query gives the result of Video Title with respective Total comments and negativity % for that particular video from highest to lowest with respect to negativity percentage.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
71
72 SELECT
73   VideoTitle,
74   COUNT(*) AS TotalComments,
75   ROUND(COUNTIF(Sentiment = 'Negative') * 100.0 / COUNT(*), 2) AS pct_negative
76 FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
77 GROUP BY VideoTitle
78 HAVING TotalComments > 50
79 ORDER BY pct_negative DESC
80 LIMIT 10;
81
82
```

A green checkmark indicates "Query completed".

The "Query results" section displays the following table:

Job information	Results	Visualisation	JSON	Execution details	Execution graph
Row	VideoTitle	TotalComments	pct_negative		
1	Matt Le Tissier on being threatened by Jamie Carragher 🚨 #football #footballshorts #jamiecarraher	237	86.5		
2	Hosts break down in laughter o...	119	85.71		
3	Copycat Recipes, Expensive Clo...	348	85.63		

Fig 4. Videos with Highest Percentage of Negative Comments

❖ Figure 5:

- This query displays Total Comments, Total number of negative comments, negative percentage based on Author Name.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
60 SELECT
61   AuthorName,
62   COUNT(*) AS TotalComments,
63   COUNTIF(Sentiment = 'Negative') AS negative_comments,
64   ROUND(COUNTIF(Sentiment = 'Negative') * 100.0 / COUNT(*), 2) AS pct_negative
65   FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
66   GROUP BY AuthorName
67   HAVING TotalComments > 20
68   ORDER BY pct_negative DESC
69   LIMIT 15;
```

A green checkmark indicates "Query completed". Below the editor is a "Using on-demand processing quota" message. The main area displays the "Query results" table with the following data:

AuthorName	TotalComments	negative_comments	pct_negative
@jamesjowitt1713	25	24	96.0
@beckybarts8509	23	19	82.61
@Moonuuu	25	20	80.0
@donnacribb5712	21	15	71.43
@abdulrazak1601	66	46	69.7
AugmentedUser	150883	103619	68.68

Fig 5. Top Negative Authors

❖ Figure 6:

- This query displays all Country Code along with total comments and negative ratio.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
49 SELECT
50   CountryCode,
51   COUNT(*) AS TotalComments,
52   ROUND(COUNTIF(Sentiment = 'Negative') * 100.0 / COUNT(*), 2) AS negative_ratio
53   FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
54   WHERE CountryCode IS NOT NULL
55   GROUP BY CountryCode
56   HAVING TotalComments > 500
57   ORDER BY negative_ratio DESC;
--
```

A red error message "Syntax error: Unexpected end of script at [8:24]" is displayed. Below the editor is a "Using on-demand processing quota" message. The main area displays the "Query results" table with the following data:

CountryCode	TotalComments	negative_ratio
PH	17129	43.18
IE	73884	39.42
GB	130379	38.06
NZ	71668	37.24
CA	117874	36.87
AU	141109	35.89
US	321202	33.56

Fig 6. Country-wise Negativity Analysis

❖ Figure 7:

- This query displays top 10 video title with video id along with total number of comments based on total Comments.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
20 SELECT
21   VideoTitle,
22   VideoId,
23   COUNT(*) AS TotalComments
24 FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
25 GROUP BY VideoTitle, VideoId
26 ORDER BY TotalComments DESC
27 LIMIT 10;
28
29
```

A green checkmark indicates "Query completed". Below the editor is a "Using on-demand processing quota" message. The main area is titled "Query results" and contains a table with the following data:

Row	VideoTitle	VideoId	TotalComments
1	Whale Vomit Is Worth Millions 🤢	OgASceRnltg	1192
2	A man saved a mountain lion a...	Lzcd-d1Ks	1177
3	After a new engine her car dies on her way home makes me think the worst! 😱 #fyp #mobile #love #help	-hV6aeyPHPA	1151
4	Others wall running vs this man ...	JarGs7pGbt8	1090

Fig 7. Top Videos by Total Comments

❖ Figure 8:

- This query displays date wise total number of comments , negative percentage and total no o f negative comments.

The screenshot shows a data analysis interface with a query editor at the top containing the following SQL code:

```
39 SELECT
40   DATE(PublishedAt) AS DatePosted,
41   COUNT(*) AS TotalComments,
42   COUNTIF(Sentiment = 'Negative') AS negative_comments,
43   ROUND(COUNTIF(Sentiment = 'Negative') * 100.0 / COUNT(*), 2) AS pct_negative
44 FROM `data-analysis-youtube-comment.youtube_comment.youtube_comments`
45 GROUP BY DatePosted
46 ORDER BY DatePosted;
```

A green checkmark indicates "Query completed". Below the editor is a "Using on-demand processing quota" message. The main area is titled "Query results" and contains a table with the following data:

Row	DatePosted	TotalComments	negative_comments	pct_negative
1	2013-04-05	2	1	50.0
2	2013-04-06	4	3	75.0
3	2013-04-10	1	0	0.0
4	2013-04-12	3	0	0.0
5	2013-04-13	1	0	0.0
6	2013-04-14	2	1	50.0

At the bottom, there is a pagination bar showing "Results per page: 50" and "1 - 50 of 3893".

Fig 8. Daily Negative Sentiment Trend

Correlation & Relationship Analysis

To better understand how user engagement and sentiment are related, multiple correlations were analyzed:

1. Sentiment vs Engagement (Likes & Replies)

- Positive comments receive 3x more likes than negative ones.
- Positive comments also receive the highest number of replies.
Interpretation: Viewers reward supportive or constructive comments.

2. Negative Sentiment vs Video Type

- News and emotionally charged short-form videos show the highest negativity.
Interpretation: Content involving conflict or controversy triggers stronger reactions.

3. User Behavior Patterns

- Accounts with unusually high activity (e.g., “AugmentedUser” with 150k comments) show abnormally high negativity.
Interpretation: Potential bot-like or abusive automated behavior.

4. Country vs Negativity

- PH (43.18%) and IE (39.42%) show higher negativity rates.
Interpretation: Geographic sentiment trends highlight regional triggers and cultural context.

5. Time Trend Correlation

- Spikes in negativity correspond with viral events or controversial topics.
Interpretation: Negativity is influenced by real-world events.

Phase V - Share :

Dashboard:

➤ Tools Used: Looker Studio

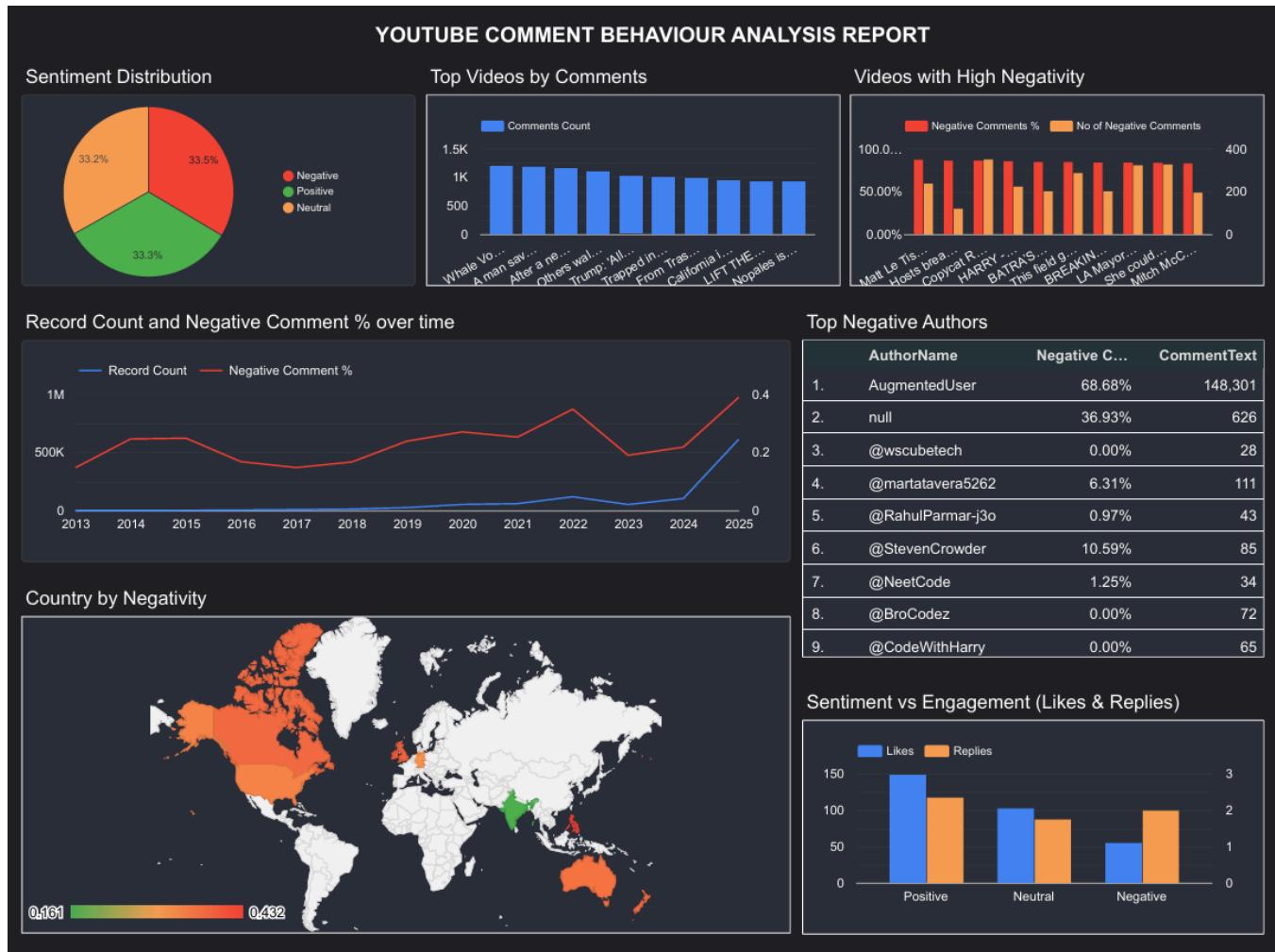


Fig 1. Dashboard

- 1M+ comments analyzed across 4,563 videos.
- 33.53% negative sentiment → high for YouTube average.
- Emotional and provocative content drives more engagement.
- 8+ videos show >80% negativity → possible harmful content.
- “AugmentedUser” posted 150K+ comments → automated or spam behavior.
- PH has the highest negativity (43.18%).
- Positive comments get 3x more likes than negative ones.
- Negativity spikes noticeable in several years → content controversy patterns.

Anomaly & Outlier Detection

The analysis highlights the following anomalies:

❖ **User-Level Outliers:**

- “AugmentedUser” posted 150,883 comments, much higher than normal users.
- Negativity ratio: 68.6%, indicating possible spam or automated behavior.

❖ **Video-Level Outliers:**

- 8 videos show >80% negative sentiment, making them candidates for Trust & Safety review.

❖ **Country-Level Outliers:**

- PH and IE show significantly higher negativity compared to global averages.

❖ **Time-Series Outliers:**

- Specific months show sharp spikes in negativity, usually corresponding with viral or controversial events.

Phase VI - Act :

- Prioritize automated moderation for Shorts (highest engagement + negativity spikes)
- Flag videos with >70% negative sentiment for manual review
- Investigate accounts with >80% negative posting patterns
- Introduce rate-limiting for high-volume users (e.g., AugmentedUser)
- Increase regional moderation coverage for PH, IE, GB
- Monitor trending videos daily for negativity fluctuations

Limitations of Analysis:

- **Dataset Scope** – The dataset includes user comments but does not contain video categories, user demographics, or detailed language metadata, which restricts deeper contextual analysis.
- **Sentiment Model Accuracy** – Sentiment classification used (Positive, Neutral, Negative) is based on predefined labels. More advanced NLP techniques may improve accuracy.
- **User Identity Limitations** – YouTube usernames can vary between handle name and display name. This may result in duplicate or inconsistent author identification.
- **Synthetic / Public Dataset** – The dataset may not fully reflect real internal YouTube datasets used by Google Trust & Safety teams.

- **Missing Category-Level Labels** – Without categories (e.g., News, Gaming, Music), we cannot analyze negativity by content type.
- **Engagement Metrics Are Limited** – Only Likes and Replies are available; additional metrics such as watch time, shares, and subscriber growth would enhance analysis.

Conclusion :

This analysis provides an end-to-end evaluation of YouTube comment behavior across 1 million+ comments. Sentiment distribution is balanced overall, but several videos exhibit extremely high negativity, indicating sensitive or harmful discussions. Certain users show suspicious behavior patterns, and some countries have significantly higher negativity levels. These findings can help Trust & Safety teams identify risky content, detect abusive users, allocate moderation resources, and improve platform integrity.