Course Title: Applied Analytical for Tech Management (TIMG 5301)

Assignment Title: Report #2 — Topic Modeling and Analytical Trends on Snapchat

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Introduction

With the rapid expansion of social media, platforms such as Snapchat have become major venues for user interaction, self-expression, and feedback. As of 2024, Snapchat reported approximately 422 million daily active users, increasing to about 453 million by early 2025, underscoring the scale of user-generated comments suitable for large-scale text analytics (Reuters, 2024; Snap Investor Relations, 2025). Such user-generated data provide a valuable corpus for understanding real-time user opinions and attitudes, a premise central to sentiment analysis and opinion mining (Liu, 2012).

This project aims to preprocess, clean, and analyze a corpus of roughly 50,000 user comments related to Snapchat, applying text-analytics methods to uncover dominant discussion topics and associated sentiments. The analysis not only quantifies overall emotional tone but also links sentiment to specific topics, aligning with evidence that joint/topic-aware sentiment methods yield more actionable and context-relevant insights than corpus-level sentiment alone (Lin & He, 2009; Li et al., 2010).

Accordingly, the study is guided by the following research questions:

- **RQ1.** What are the key topics emerging from user comments about Snapchat?
- **RQ2.** How do user sentiments manifest at both the overall corpus level and within specific discussion topics?
- **RQ3.** Which managerial insights can be derived from the detected topics and sentiments to enhance user engagement and brand perception?

By addressing these questions, the project contributes to a deeper understanding of user perceptions toward Snapchat and demonstrates the application of text mining for extracting interpretable insights from large-scale social-media data.

1. Data and Methodology Overview

1.1 Dataset Description

The dataset used in this study consists of approximately 50,000 user comments related to Snapchat, representing spontaneous user feedback and discussion extracted from public social-media sources. Each record contains a short free-text comment, varying from single-word reactions to multi-sentence narratives that express user opinions, emotions, or experiences with the platform.

1.2 Data cleaning

Before conducting text analysis, a comprehensive data-cleaning process was implemented to ensure the integrity and interpretability of the corpus. During cleaning, two main actions were performed: (1) removal of invalid or non-informative comments, and (2) correction of comments that contained minor issues but retained analytical value. This process helped preserve meaningful user input while ensuring linguistic consistency.

a. Comments excluded from the dataset

A total of 6,376 comments (≈12.8%) were excluded from the dataset. Comments were removed if they were written in non-English languages, contained spam or irrelevant promotional material, were unreadable, or consisted only of emojis or symbols. These removals targeted noise that could distort topic and sentiment detection.

Table 1: Number of removed comments

Category	Description	# of Comments Removed
Foreign language	Non-English reviews (e.g., French, Spanish)	2,879
Irrelevant / spam	Off-topic or promotional content	1,860
Unreadable text	Distorted or nonsensical entries	95
Emoji-only comments	Contain only emojis or symbols	1,542
Total Removed		**6,376**

b. Comments standardized and corrected

In addition, 7,075 comments (≈14.1%) were corrected to retain valuable user information. Corrections addressed emoji normalization and minor spelling inconsistencies. For example, *"Nice 🥰"* was standardized as *"Nice"*, and *"goodddd"* was normalized to *"good."*

Table 2: Number of corrected comments

Category	Description	# of Comments Corrected
Emoji correction	Emojis removed, text kept (e.g., "Nice 😍" → "Nice")	5,807
Spelling correction	Minor typographical errors fixed (e.g., "goodddd" → "good")	723
Combined correction	Cleaned for both emoji and spelling	545
Total Corrected		**7,075**

After cleaning, the dataset contained **43,624 valid comments** suitable for preprocessing and text-mining analysis. This process ensured that the final corpus preserved authentic user expressions while minimizing non-linguistic noise, a crucial step to enhance topic interpretability and sentiment reliability in later analytical stages.

1.3 Preprocessing and Text Normalization

After data cleaning, the corpus of **43,624 valid comments** was preprocessed using **Orange Data Mining** to prepare the text for analysis. The preprocessing pipeline aimed to standardize text format, remove noise, and retain only linguistically meaningful tokens for subsequent modeling.

The process included lowercase conversion, accent and URL removal, HTML parsing, tokenization, and lemmatization. Texts were tokenized using whitespace and regular-expression patterns to ensure clean segmentation of meaningful words while excluding punctuation and symbols. The **WordNet lemmatizer** was then applied to normalize word forms (e.g., *"running"* → *"run"*) and preserve semantic consistency, producing linguistically accurate representations suitable for topic modeling and sentiment analysis.

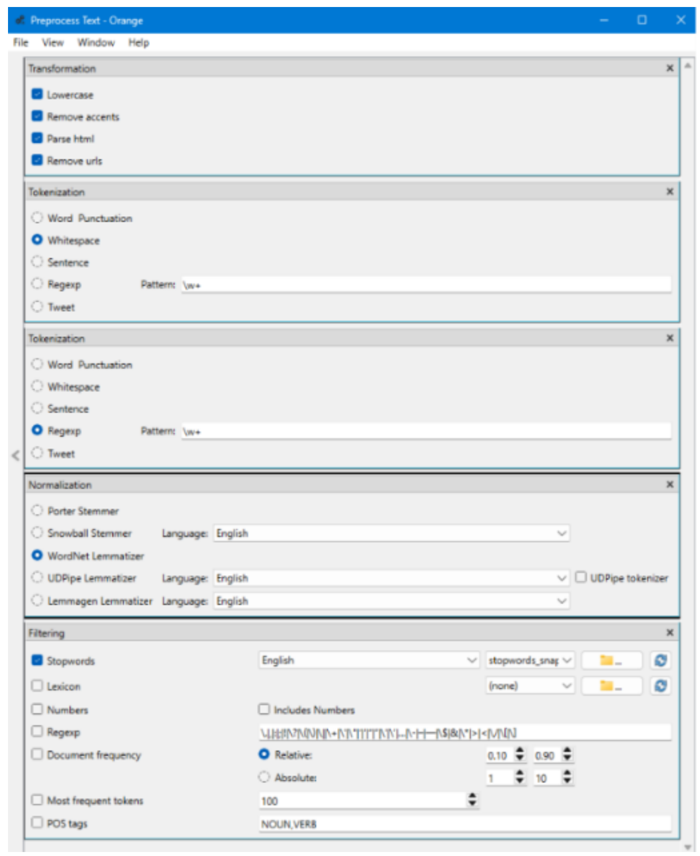

Figure 1 Orange preprocess text

For stopword filtering, A two-layer stopword strategy was employed to remove high-frequency but semantically uninformative words. In addition to the default English stopword list, a custom list of 264 domain-specific stopwords was created through iterative word cloud comparisons before and after filtering.

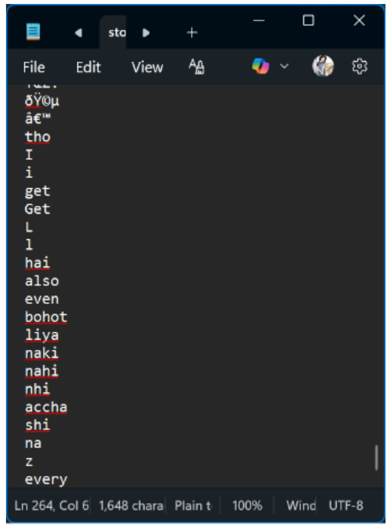

Figure 1 Stopwords

This list included platform-related words (e.g., “snap,” “app,” “story”), residual symbols or foreign-language fragments overlooked during cleaning, and overly generic or non-semantic terms. Removing these context-irrelevant tokens improved the clarity and distinctiveness of the extracted topics, allowing the analysis to concentrate on linguistically coherent and conceptually meaningful content.

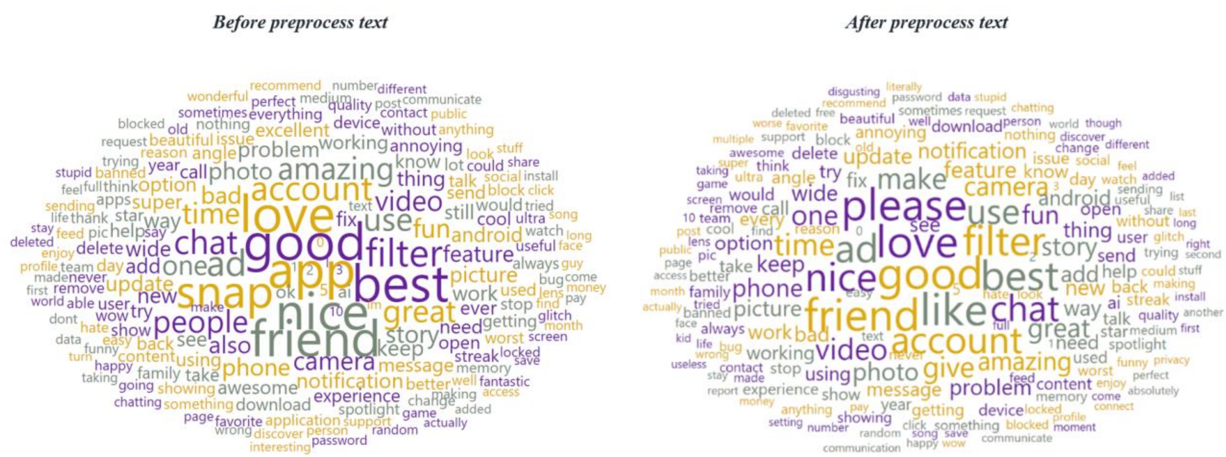

Figure 2 Word cloud before and after preprocess text

2. Analytical Framework

To uncover both thematic and emotional patterns within the corpus, the study employed a computational text-analytics framework integrating topic modeling, sentiment analysis, and visualization.

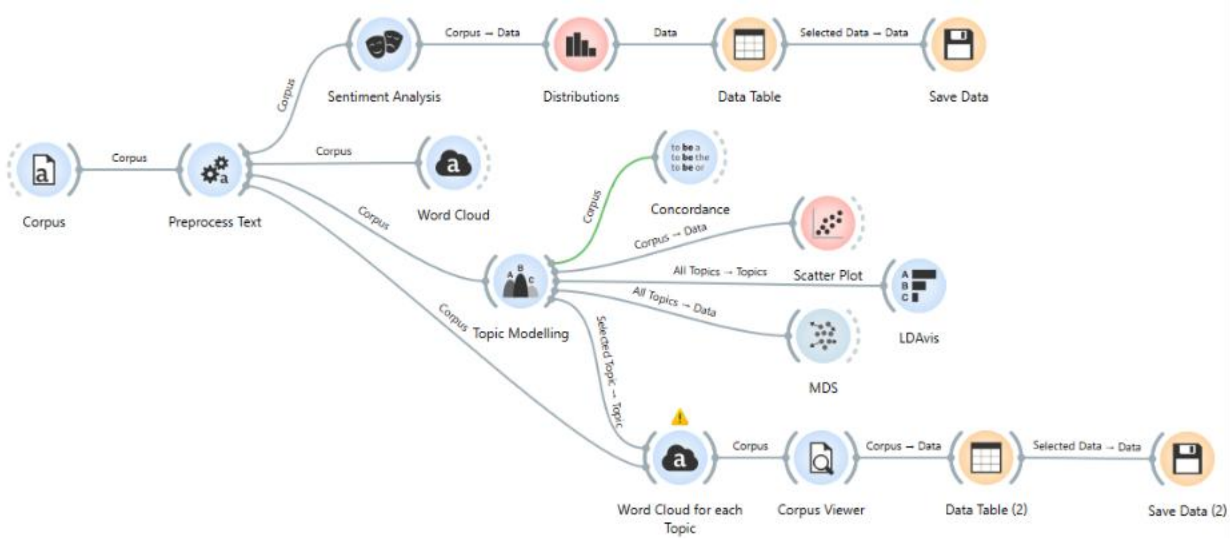

Figure 3 Orange Data Mining workflow for Snapchat data analysis

Topic modeling was implemented using the Latent Dirichlet Allocation (LDA) algorithm, which identifies latent semantic structures by clustering words that frequently co-occur across documents (Blei et al., 2003). This method enables the discovery of recurring discussion themes without prior labeling, providing an unsupervised understanding of how users talk about Snapchat.

Sentiment analysis was applied using a lexicon-based approach to quantify emotional polarity at two levels: the overall corpus and within each topic subset. This dual-level analysis captures both general user attitudes and topic-specific sentiment nuances, allowing for a richer interpretation of emotional tone (Liu, 2012).

Visual analytics tools including Word Cloud, LDAvis, and Multidimensional Scaling (MDS) were used to support interpretability by illustrating topic relationships, key terms, and sentiment distributions. Together, these techniques form a reproducible pipeline for translating large-scale unstructured text into interpretable and decision-relevant insights.

2.1 Corpus exploration and sentiment overview

Sentiment analysis was conducted on the cleaned corpus using the VADER (Valence Aware Dictionary and sEntiment Reasoner) by Hutto & Gilbert (2014) implemented in Orange Data Mining. VADER assigns each text a compound score between –1 (most negative) and +1 (most positive), making it suitable for short, informal language typical of social-media discourse.

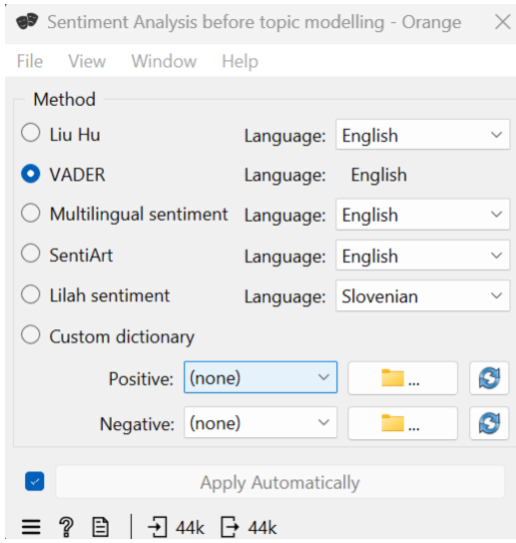

Figure 4 Sentiment analysis settings in Orange using the VADER algorithm

As shown in Figure 6, the sentiment distribution is skewed toward the positive side, with a dominant cluster between +0.4 and +0.6, indicating generally favorable attitudes toward Snapchat. A considerable share of comments falls near 0.0, representing neutral or weakly emotional reactions, while only a small portion shows negative polarity (–0.4 to –0.6). This pattern suggests that most user feedback is either mildly positive or emotionally neutral rather than strongly polarized. The limited emotional intensity may be influenced by the brevity of user comments, many being short expressions such as *"nice," "love," "cool"*, that inflate positive or neutral scores without adding meaningful context.

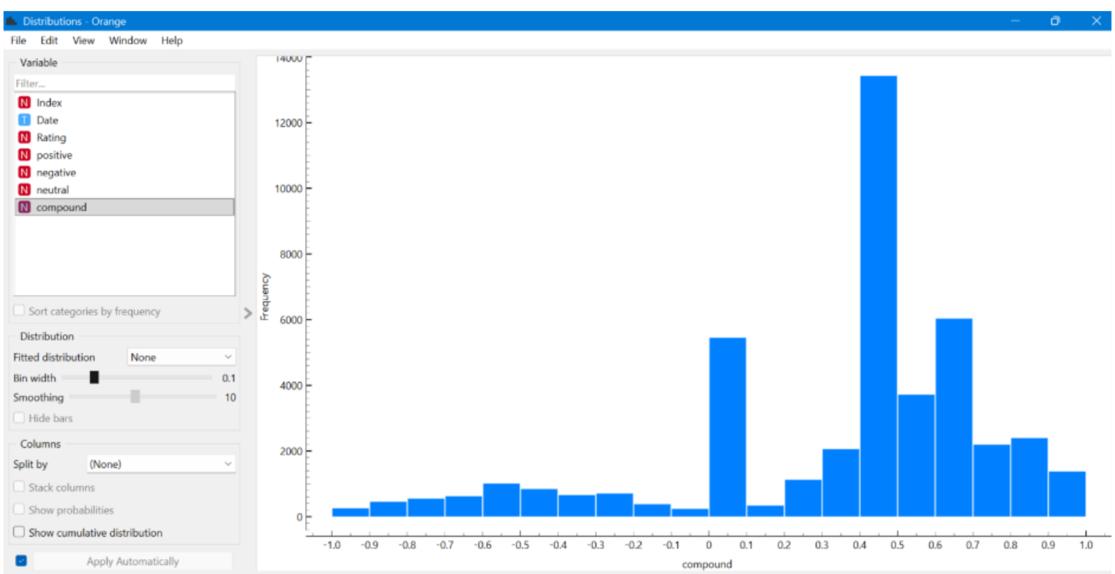

Figure 5 Distribution of compound sentiment scores (n = 43,627 comments)

To better understand the limited polarity strength observed in the corpus-level sentiment distribution, the length of user comments was examined as a proxy for expressiveness and semantic richness. As shown in Figure 7 the corpus is dominated by short entries: 85.4% of all comments contain fewer than 20 words, and nearly 28.5% consist of only a single word. The frequency decreases sharply as length increases, confirming that most user input is brief and low in semantic richness.

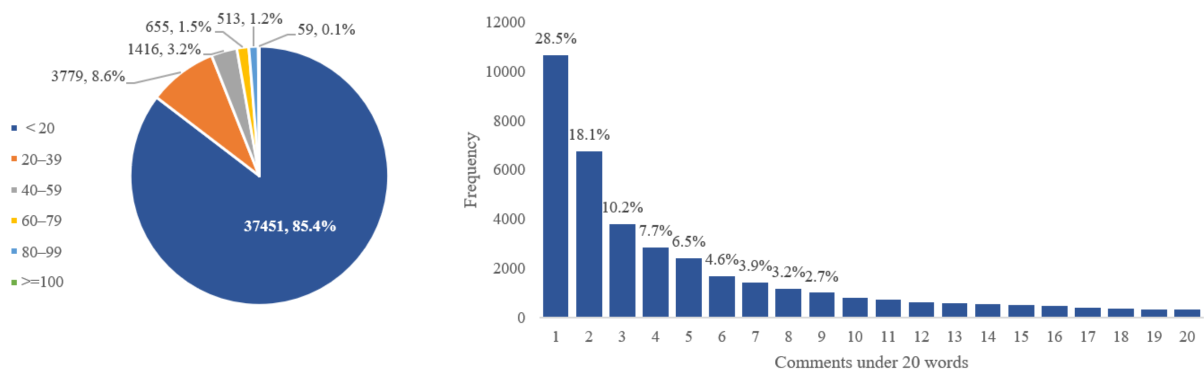

Figure 6 Comment length distribution (n = 43,627 comments)

Further analysis of the relationship between sentiment and comment length (Figure 8) reveals a U-shaped pattern. Both highly negative and highly positive comments are considerably longer on average, while neutral ones are the shortest. This indicates that stronger emotions prompt users to express themselves more elaborately, whereas neutral reactions are often limited to brief acknowledgments or emojis. (Thelwall, 2017).

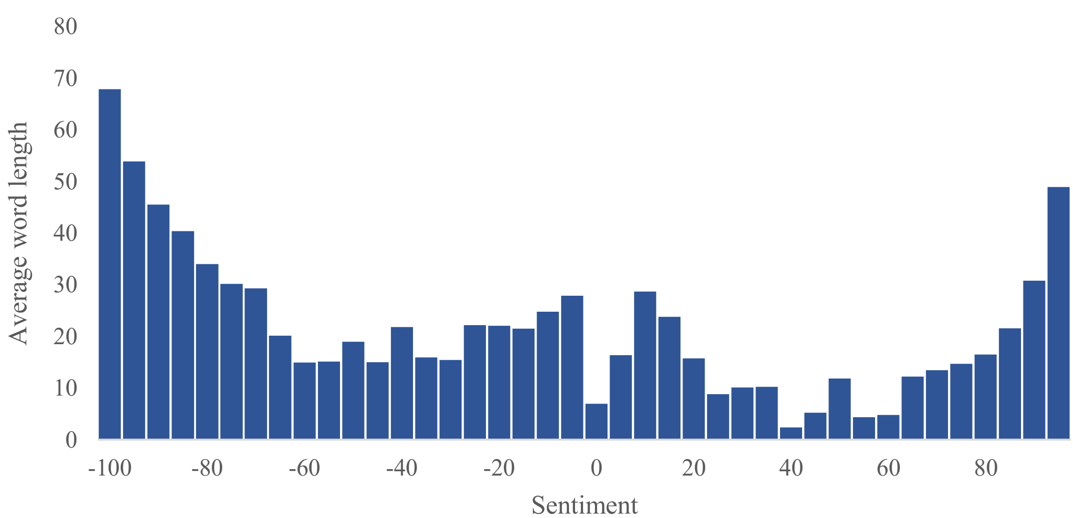

Figure 7 Sentiment distribution by comment length

To minimize noise and improve semantic clarity, all comments containing fewer than three tokens were removed prior to topic modeling. This step eliminated 17,348 entries (46% of the corpus), which largely consisted of affective interjections such as *"nice," "cool,"* or *"love it"* - phrases lacking syntactic or contextual depth. Prior research supports this threshold, showing that extremely short texts contribute little to topic coherence and may distort word–topic distributions (Schofield et al., 2017).

Empirical inspection confirmed that comments of three words or more began to convey clear intent (e.g., *"filters is great," "I hate advertising"*), justifying their inclusion. As short comments were disproportionately tied to 5-star ratings (Figure 9), their removal reduced superficial positivity while preserving underlying sentiment trends. Although this trade-off may slightly shift the corpus toward neutrality, it results in a more interpretable and reliable foundation for topic discovery.

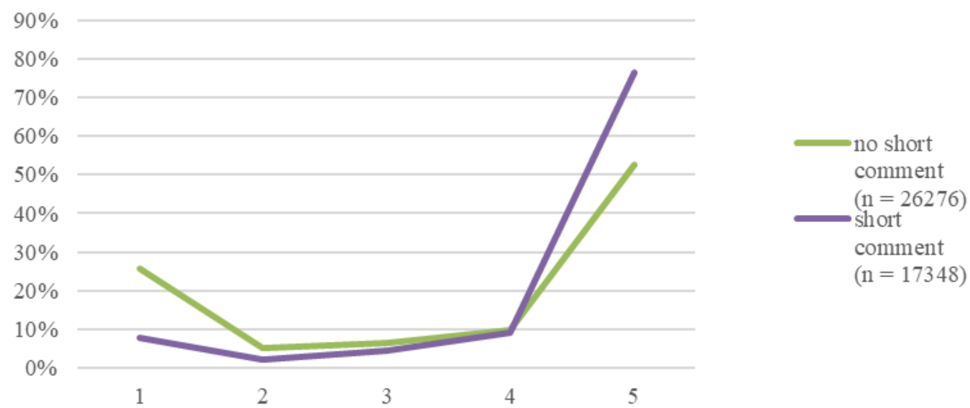

Figure 8 Rating distribution by corpus (short vs. no short comments)

Building on this refined corpus, a temporal comparison of average sentiment and user ratings (Figure 10) revealed a notable divergence: ratings showed a gradual upward trend, whereas sentiment scores declined. This inconsistency raises an important interpretive question: does it indicate genuine improvement in user satisfaction, or a growing gap between how users rate the app and how they articulate their experiences in text?

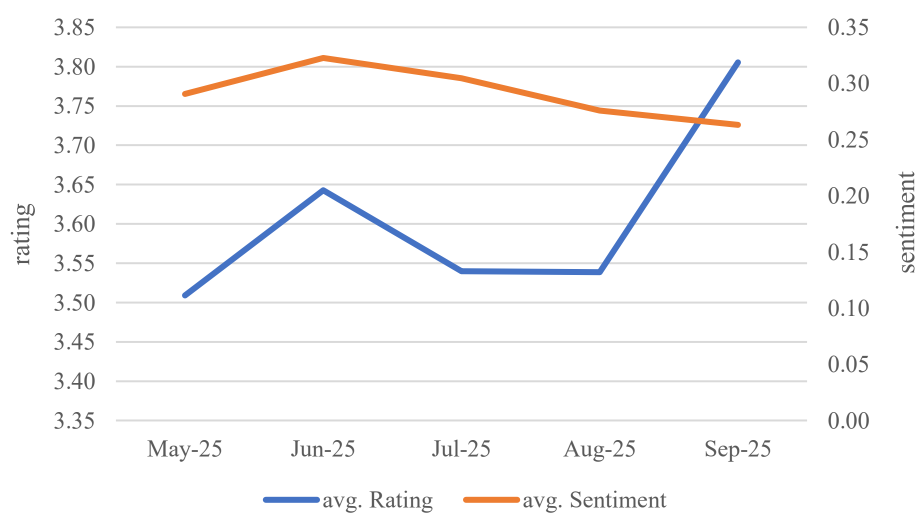

Figure 9 Average sentiment and rating over time

Such divergence may stem from contextual factors for instance, updates that enhanced functionality and drove higher ratings while simultaneously prompting frustration about advertising or usability, which is reflected in written comments. To clarify these dynamics, the next stage employs topic modeling to uncover key discussion themes and analyze how sentiment and ratings evolve within those topics over time.

3. Topic Modelling

After completing sentiment analysis, we applied Latent Dirichlet Allocation (LDA) to uncover the underlying themes in user reviews (Blei et al., 2003). LDA groups frequently co-occurring words into topics, allowing each review to be represented as a mixture of overlapping themes (e.g., technical bugs, ads interference). Our objectives were (1) to identify the core themes driving user sentiment and (2) to assess how strongly each topic relates to user satisfaction by linking topics to sentiment scores.

Using Orange, we tested models with 3–14 topics and selected the optimal number based on topic coherence, log perplexity, Kruskal stress, and interpretability. For each candidate model, we reviewed top terms and sample reviews to ensure meaningful patterns.

3.1 Evaluating Topic Model Performance: Topic Coherence, Kruskal Stress, and Log Perplexity Trends

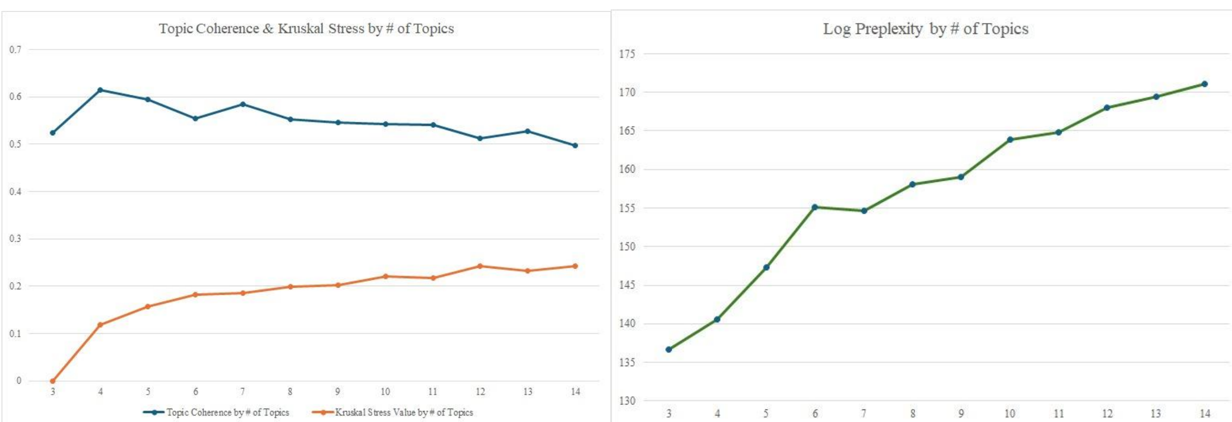

Figure 11: Topic Coherence, Kruskal and Log Perplexity of 14 Topics

Topic Coherence measures how meaningful the words in a topic are. A higher coherence score suggests that words are more likely to appear together in documents, making the topic easier to interpret. The 4-topic model achieves the highest coherence (0.61837), indicating clear word-grouping. However, as more topics are added, coherence decreases, particularly after 5 topics, causing themes to fragment and become harder to interpret.

Kruskal Stress Value measures how well the topic relationships are represented in 2D space. The steady increase in stress from 0.000 at 3 topics to 0.232 at 14 topics shows that more topics result in greater distortion, reducing clarity in the layout.

Log Perplexity assesses predictive accuracy, with lower values indicating better performance. The increase in log perplexity from 137.24623 at 3 topics to 168.86391 at 14 topics suggests that as more topics are added, the model's performance declines, indicating reduced confidence in the predictions.

3.1.1 Why 5 Topics Were Selected Instead of Other Topics:

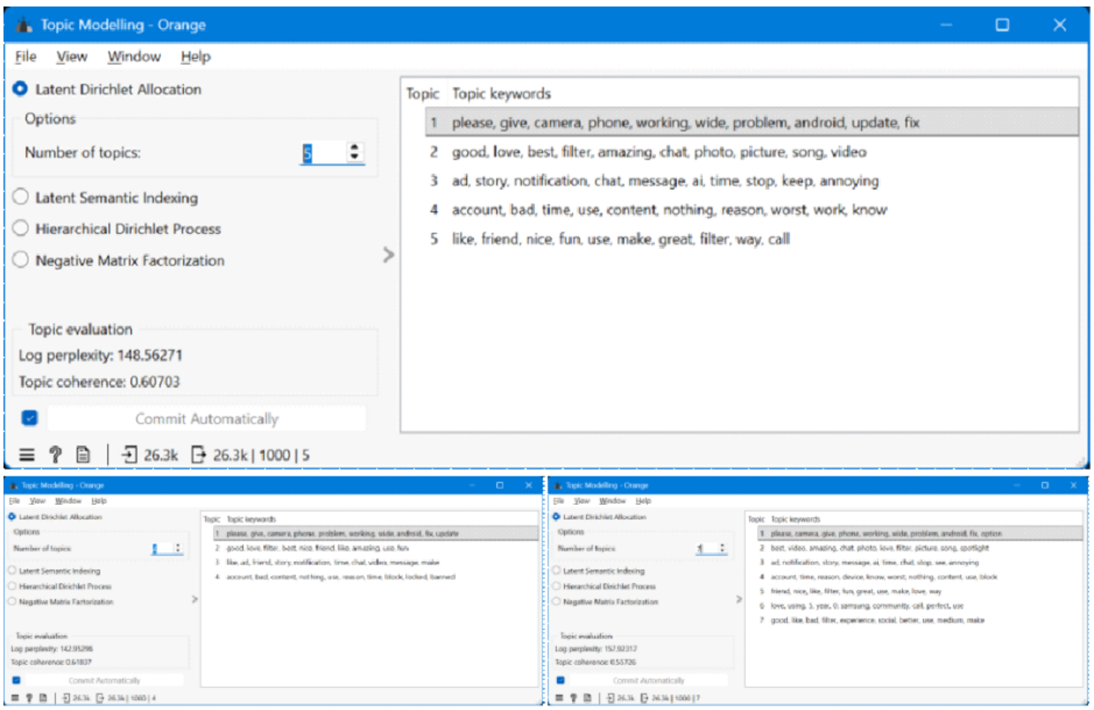

Figure 12: Topic Modelling for 4,5 & 7 Topics

The selection of **5 topics** for topic modeling is based on a balance between **topic coherence** and **interpretability**. As seen in the analysis:

- **Topic Coherence** peaks at **4 topics** but declines as the number of topics increases. With **5 topics**, coherence remains relatively high (**0.60703**) while providing more distinct, interpretable themes. This is crucial because adding too few topics (e.g., **3** or **4 topics**) results in **blended** themes that are too broad, while more than **5 topics** leads to **fragmentation** and reduced clarity.

- The **Kruskal Stress Value** and **Log Perplexity** also show that adding more than **5 topics** leads to diminishing returns, with increasing **stress values** and **higher perplexity**, indicating that the model is becoming **less reliable** with a greater number of topics.

Therefore, **5 topics** were selected as the optimal choice. It balances **clarity** and **coherence** without causing the fragmentation seen at **6+ topics**, ensuring **meaningful themes** for in-depth analysis.

3.2 Topic Identification, Labelling & Interpretation

We identified and labeled each topic by examining the most frequent and representative terms that co-occur in user reviews, along with the average rating associated with each theme. The top terms revealed the underlying subject matter, such as “camera,” “wide,” “phone,” and “android” in Topic 1, which clearly point to device and camera issues. This labeling process also supports interpretation by linking themes to user sentiment: terms like “crash” and “freeze” indicate frustration, whereas words such as “love,” “best,” and “amazing” reflect positive experiences with Snapchat’s features.

Table 3-Summarizes the five initial topics and their highest-weight keywords:

Topic #	Initial Topic Label	Top Terms
1	Technical Issues & Device Performance	please, give, camera, phone, working, wide, problem, android, update, fix
2	Creative Features & Positive Experience	good, love, best, filter, amazing, chat, photo, picture, song, video
3	Ads, Notifications & UX Annoyances	ad, story, notification, chat, message, ai, time, stop, keep, annoying
4	Account, Login & Support Problems	account, bad, time, use, content, nothing, reason, worst, work, know
5	Social Connection & Positive Usage	like, friend, nice, fun, use, make, great, filter, way, call

Table 3: Topic Labelling and Top Terms

These topics, each represented by the ten highest-weight keywords, form the foundation of our analysis. They are visualized using word clouds and LDAvis, and further examined through concordance-based interpretation of user comments in the following sections.

3.3 LDAvis & Word Cloud of Each Topic

LDAvis visualizations for each topic revealed dominant terms that characterize the topic. For example, Topic 1’s (*Technical Issues & Device Performance)* was dominated by terms like “camera”, “phone”, “working” and ”wide” while (*Creative Features & Positive Experience)* prominently featured words like “love,” “best,” and “filter.”

3.3.1 Deep Dive on the Topic Narratives using LDAvis, Word Cloud and Concordance

Topic 1: Technical Issues & Device Performance:

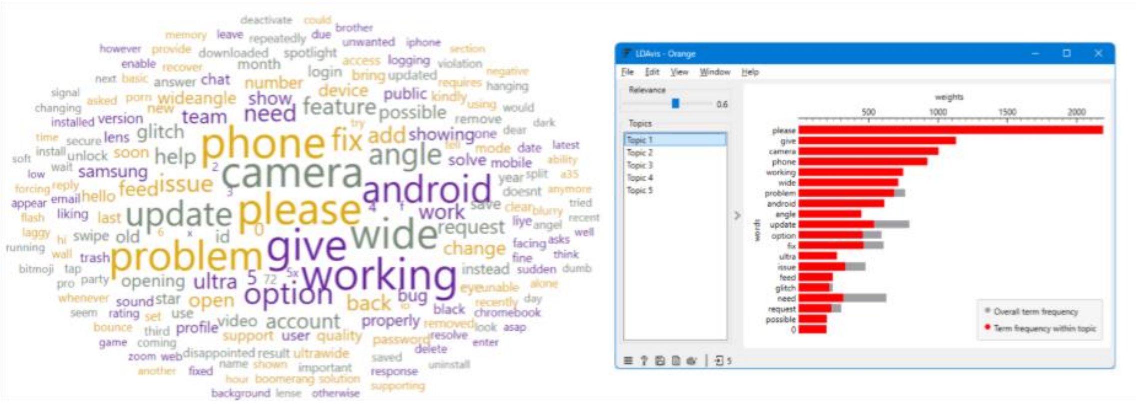

Figure 13: LDAvis & Word Cloud of Topic 1

In terms of sentiment, both the LDAvis and the word cloud highlight keywords such as "please," "problem," "fix," and "issue," which indicate that this topic leans strongly negative.

For topic interpretation, keywords such as *camera*, *phone*, and *Android* suggest that the cluster is related to camera performance on specific devices.

Concordance-Based Interpretation (Text Evidence)

To clarify the meaning of less explicit terms like *"wide," "angle,"* and *"working,"* we conducted a concordance analysis to examine real usage contexts.

From the concordance results, we observed highly consistent patterns:

- "Please give wide angle on Android"
- "Give me ultra-wide angle on Snapchat"
- "Not working 0.5x lens in my device"
- "Wide angle feature removed for Android"
- "Please fix ultra-wide issue"

These examples demonstrate that the cluster is driven by users requesting missing camera features, complaining about malfunctioning wide-angle lenses, or asking Snapchat to fix compatibility and lens issues specifically on Android devices. Given this evidence, *Camera Issues* is a more accurate and comprehensive refined label for this topic.

Topic 2: Creative Features & Positive Experience:

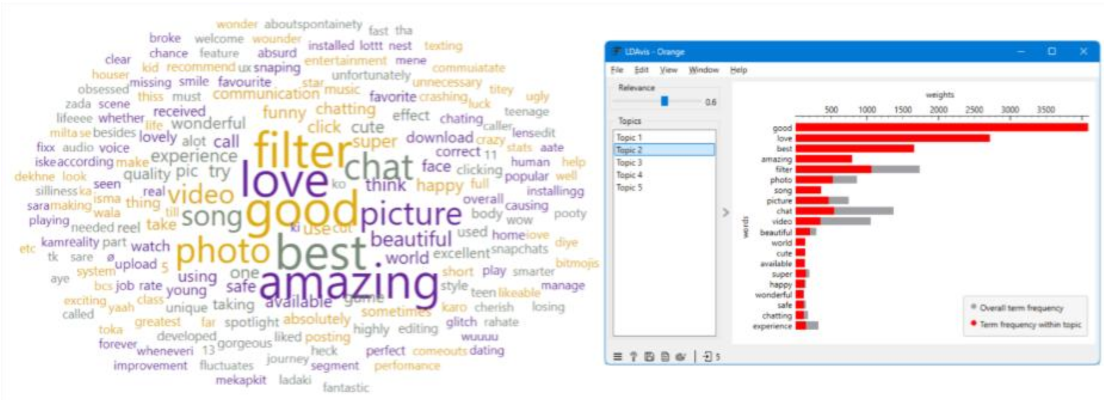

Figure 14: LDAvis & Word Cloud of Topic 2

LDAvis surfaces “love,” “best,” “filter,” “amazing,” and “photo” as dominant. Word clouds reinforce a strong positive tone, and concordance around “use” and “way” shows people describing Snapchat as their preferred way to share pictures and have fun with friends.

Concordance-Based Interpretation (Text Evidence)

To validate the label, we examined the concordance results for top keywords such as “love,” “filter,” “chat,” and “amazing.” The concordance shows hundreds of near-identical patterns:

- “I love Snapchat, just that I really wished my camera would work”
- “Filters on Snapchat are awesome”
- “Snapchat is a great way to chat with friends”
- “I had an amazing experience using the app”

These examples demonstrate that the cluster is driven by users expressing positive sentiment toward the app, especially its core features like chatting, filters, and overall experience. Therefore, a more suitable refined label for this topic is “User Enjoyment,” as the evidence shows that it not only captures positive reactions to specific creative features but also reflects broader expressions of overall satisfaction, such as users describing Snapchat as “a great way to chat with friends,” which represents a positive experience beyond any single feature.

Topic 3: Ads, Notifications & UX Annoyances:

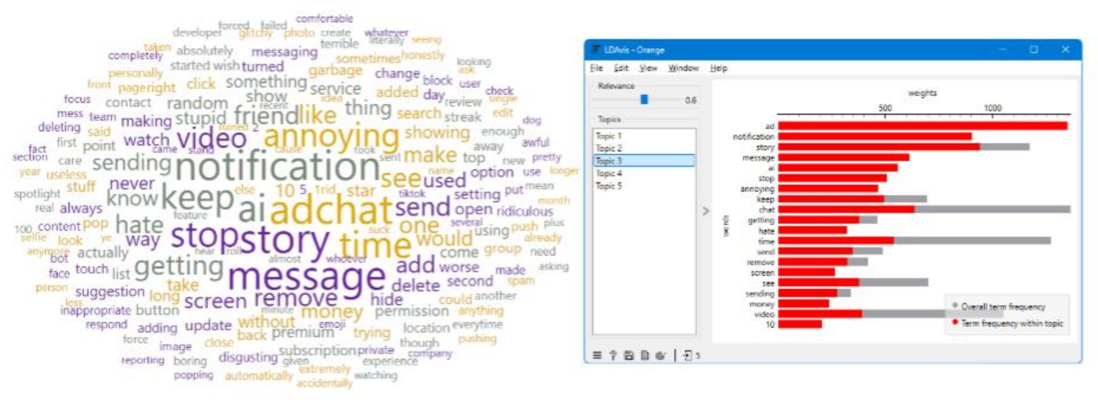

Figure 15: LDAvis & Word Cloud of Topic 3

In terms of sentiment, both the LDAvis and the word cloud reveal keywords such as "annoying," "stop," "keep," and "please," which signal that this topic leans strongly negative. The clustering of these terms suggests persistent frustration rather than isolated inconveniences.

For topic interpretation, keywords such as "ad," "notification," and "message" indicate that the cluster relates to disruptive user experiences caused by intrusive ads and repeated notifications.

Concordance-Based Interpretation (Text Evidence)

To clarify the meaning of less explicit terms like "getting," "time," "send," and "sending," we conducted a concordance analysis to examine real usage contexts.

From the concordance results, we observed highly consistent patterns:

- "Stop sending me random ads to my inbox"
- "My stories keep getting interrupted by ads"
- "I can't send snaps to my friends"
- "I keep getting the same notifications over and over again"

These examples demonstrate that the cluster is driven by intrusive advertising, repeated notifications (often triggered by ads), and interruptions to core functions such as sending snaps and viewing stories. Users consistently describe these experiences as overwhelming, time-consuming, and highly disruptive to their normal app usage.

Given this evidence, Ad-Related Disruptions is a more accurate and comprehensive refined label for this topic.

Topic 4: Account, Login & Support Problems:

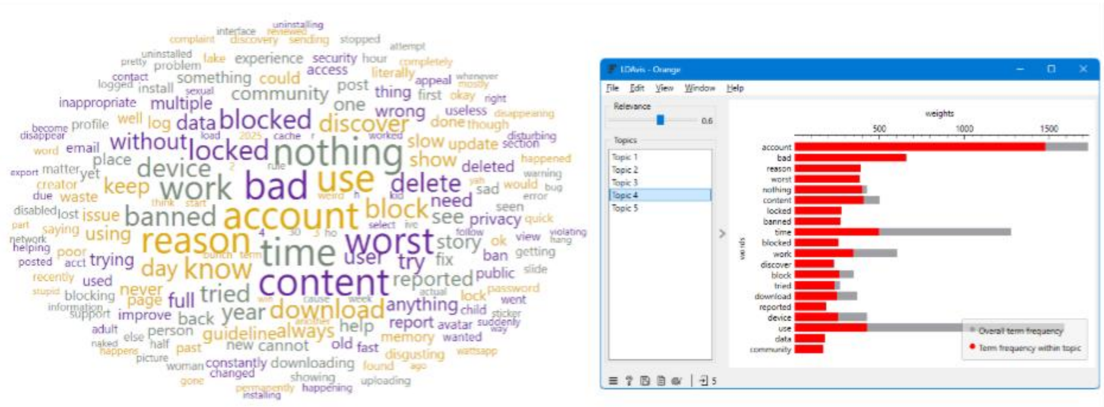

Figure 16: LDAvis & Word Cloud of Topic 4

In terms of sentiment, both the LDAvis and the word cloud reveal keywords such as "bad," "worst," "reason," "banned," "locked," "nothing," which indicates that this topic leans strongly negative. The concentration of these terms reflects high-intensity frustration, typically associated with lost access or unexplained penalties rather than mild usability issues.

Keywords like "account," "locked," "reason," "banned," "content," suggest that this topic is driven by account-related disruptions - unexpected bans, login failures, and appeals that users feel are ignored. These terms consistently appear alongside complaints about support transparency and policy enforcement, indicating friction between users and Snapchat's moderation systems.

Concordance-Based Interpretation (Text Evidence)

To clarify the meaning of less explicit terms such as "time," "use," "content," and "nothing," a concordance analysis was conducted to examine how users describe these issues in context.

Across the concordance results, we observed highly consistent patterns such as:

- "I got locked out of my account for no reason"
- "This happened so many times, Snapchat does nothing about it"
- "My account was banned even though I did nothing wrong"
- "I can't use my account… every time I try, it gets stuck"
- "There is inappropriate content everywhere but they ban me for nothing"

These examples demonstrate that the cluster is driven by repeated account lockouts, unexplained bans, and ongoing difficulties accessing or recovering accounts. Users consistently describe these experiences as unfair, confusing, and highly disruptive, emphasizing a lack of transparency in policy enforcement and limited support when issues arise.

Given this evidence, Account Access & Policy Friction is a more accurate and comprehensive refined label for this topic.

Topic 5: Social Connection & Positive Usage:

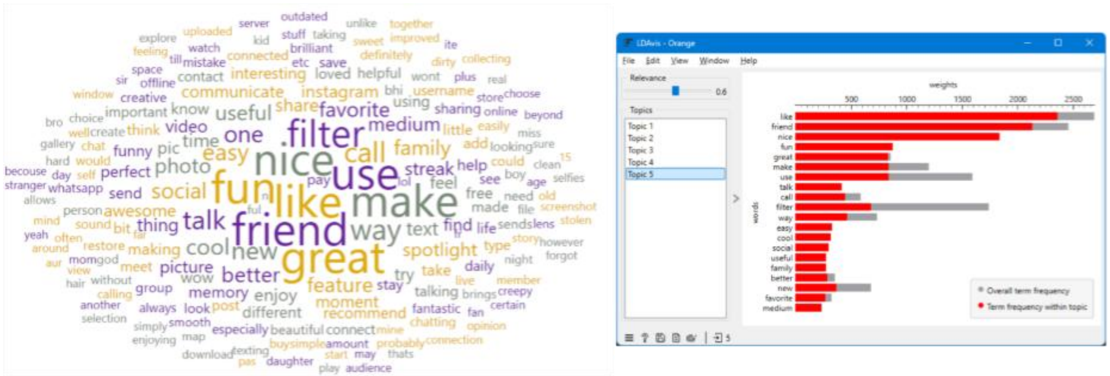

Figure 17: LDAvis & Word Cloud of Topic 5

In terms of sentiment and meaning, both the LDAvis and word cloud highlight strongly positive terms such as “great,” “fun,” “nice,” “like,” “friend,” and “call,” indicating that this topic reflects enjoyable, low-friction social communication on Snapchat. High-frequency keywords like “talk,” “use,” “filter,” and “way” reinforce that users rely on the app to connect with friends, take pictures, use filters, and stay in touch casually throughout the day. Overall, this cluster captures Snapchat’s core value proposition - simple, fun, everyday social interaction - with minimal negative sentiment compared to other topics.

This theme captures Snapchat’s core value proposition - simple, fun, everyday social communication.

Concordance-Based Interpretation (Text Evidence)

To clarify the meaning behind common but broad terms such as “use,” “filter,” “way,” and “better,” we examined concordance lines to see how users actually employ these words in full sentences.

Across the concordance results, we observed highly consistent patterns:

- “It’s a great app to use to stay connected with friends.”
- “Filters make it fun to use with people.”
- “Snapchat is a fun way to talk to your friends.”
- “It’s a better way to stay in touch than other apps.”

Given this evidence, Social Engagement is the most accurate and comprehensive refined label for this topic, capturing how Snapchat supports fun, simple, and frequent communication among friends and family.

These examples show that users consistently frame Snapchat as a positive social tool, emphasizing connection, creativity, and personal interaction. The tone is warm and appreciative, with filters, communication tools, and ease of use being recurrent reasons for satisfaction.

After completing the deep-dive analysis of concordance evidence, top keywords, we refined the initial topic labels to more accurately reflect the underlying meaning of each cluster. Combining our analytical judgment with LLM-assisted interpretation, we generated the following improved labels:

Topic #	Initial Label	Refined Label
1	Technical Issues & Device Performance	Camera Issues
2	Creative Features & Positive Experience	User Enjoyment
3	Ads, Notifications & UX Annoyances	Ad-Related Disruptions
4	Account, Login & Support Problems	Account Access & Restrictions
5	Social Connection & Positive Usage	Social Engagement

Table 4: Initial vs. Refined Topic Labels After Deep Dive

These refined labels incorporate insights from LDAvis, word clouds, and concordance, capturing more precise user pain points. To further understand how these topics relate to one another, we examined their spatial distribution using Multidimensional Scaling (MDS).

4. Topic Relationships (MDS Map Interpretation)

The MDS map revealed how the five topics relate to one another based on their co-occurrence in the reviews. Here, the circle size represents the relative prevalence of each topic in the corpus. Larger circles indicate topics that occur more frequently across reviews. For instance, Ad-Related Disruptions, Account Access & Restrictions, and Social Engagement appear as the three largest circles, highlighting their dominance in user conversations.

Topic 2 is positioned far from others because its vocabulary is semantically distinct. While Topic 5 is also positive, it focuses on social interaction, whereas Topic 2 centers on emotional praise and creative features like filters, photos, and videos. The remaining topics share more technical and complaint-oriented terms, creating higher lexical similarity among them.

Since MDS reflects word-distribution similarity rather than sentiment, Topic 2 appears isolated due to its minimal overlap with the other clusters.

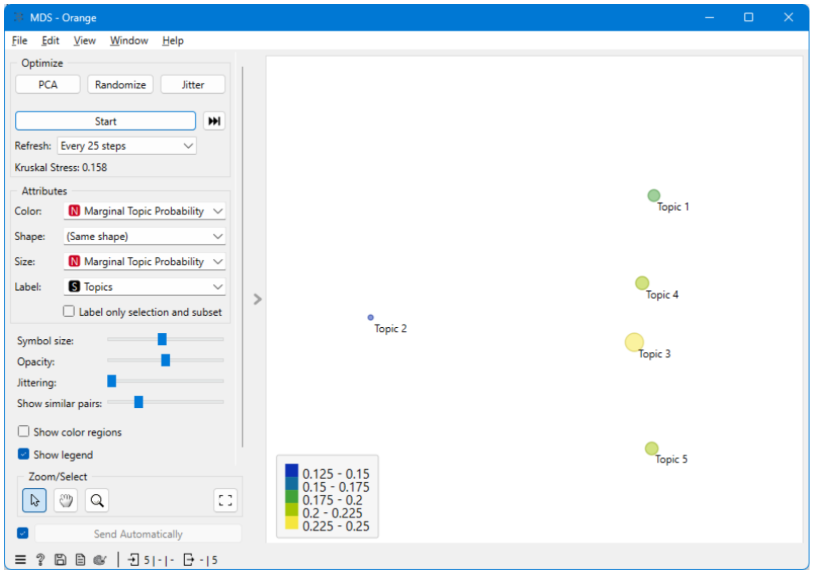

Figure 18: MDS Output

5. Trend and Findings

Key insights from the topic modeling and sentiment analysis include:

1. **Technical Issues**: Camera functionality, especially missing or malfunctioning features like wide-angle, and performance-related problems are major frustrations for users.
2. **Ads and Monetization**: Ads, notification overload, and monetization strategies disrupt the user experience and create negative sentiment.
3. **User Trust and Experience**: Account access issues, such as locks, bans, or unclear reasons, reduce user trust and cause confusion.
4. **Positive Feedback**: Positive sentiment stems from fun features like filters, chat, calling, and social interactions, while ratings often don't match users' negative feelings expressed in text.
5. **User Segmentation**: Satisfied users focus on ease of use and enjoyable features, while dissatisfied users complain about bugs, ads, and interruptions.

6. Topic evolution

Following the identification of the 5 key topics, the next step is to examine how these themes behave over time. To explore whether the prominence of any topic increases or declines, scatter plots were used to visualize topic strength across the timeline.

However, as shown in the scatter plots for all five topics, the regression slopes range only from −0.04 to +0.04, indicating minimal variation. This suggests that none of the topics exhibit a meaningful increase or decrease in prominence over the analyzed period. Instead, user discussions appear relatively stable, with consistent attention to similar themes rather than directional shifts.

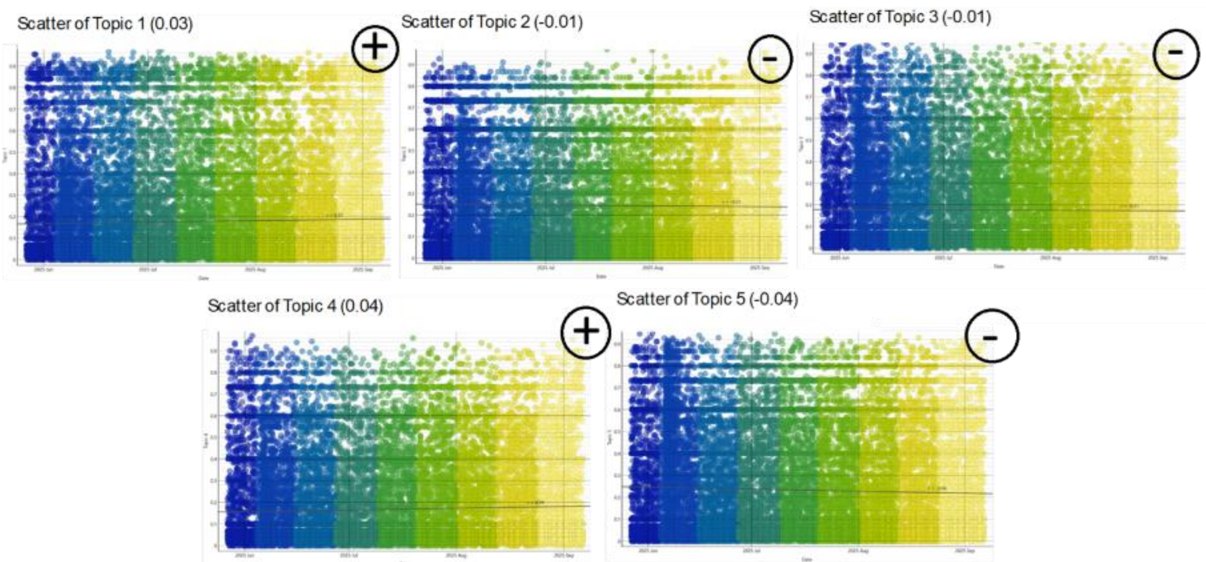

Figure 19 Scatter plot of each topic

Since topics remain stable over time, the sentiment–rating conflict must come from differences **within** topics rather than changes **between** them. When comparing topic ratings performance against the overall baseline, Topics **2 and 5** consistently outperform the overall average rating, indicating strong perceived value and positive user experience. In contrast, **Topics 3 and 4** perform below the overall rating baseline, suggesting that these themes are potential pain areas driving dissatisfaction. Topic 1 sits closer to the overall trend but fluctuates notably, indicating mixed perceptions.

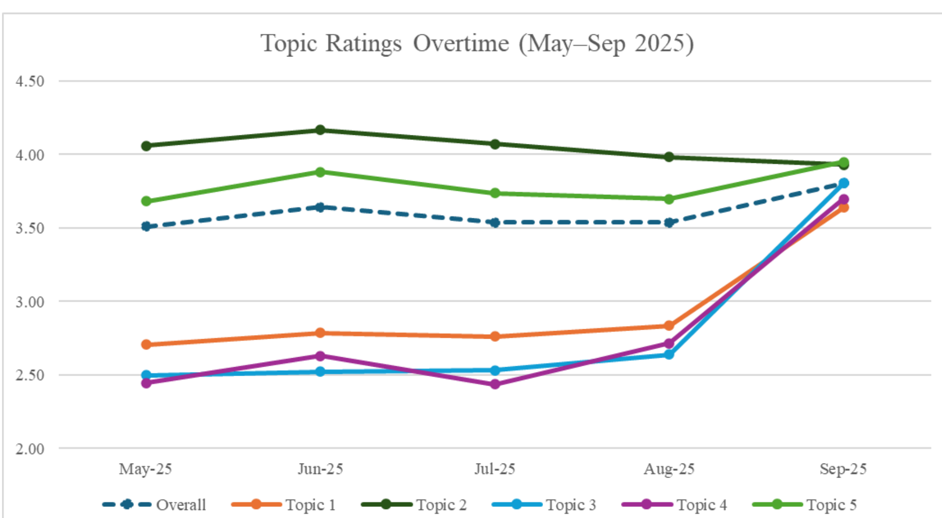

Figure 20 Overall & Topic-Level Ratings Over Time

However, when sentiment scores are examined alongside ratings, a clear misalignment emerges: although ratings for Topic 1 remain relatively high (≈3.6–3.8), sentiment for the same topic is significantly lower (≈0.10–0.15). This discrepancy indicates that many users express negative emotions or complaints in text while still assigning a high star rating - implying that ratings may reflect high-level functional satisfaction or habitual rating patterns, whereas written comments reveal unresolved frustrations. The same pattern appears across topics, demonstrating that **ratings alone can mask underlying issues** that sentiment analysis exposes.

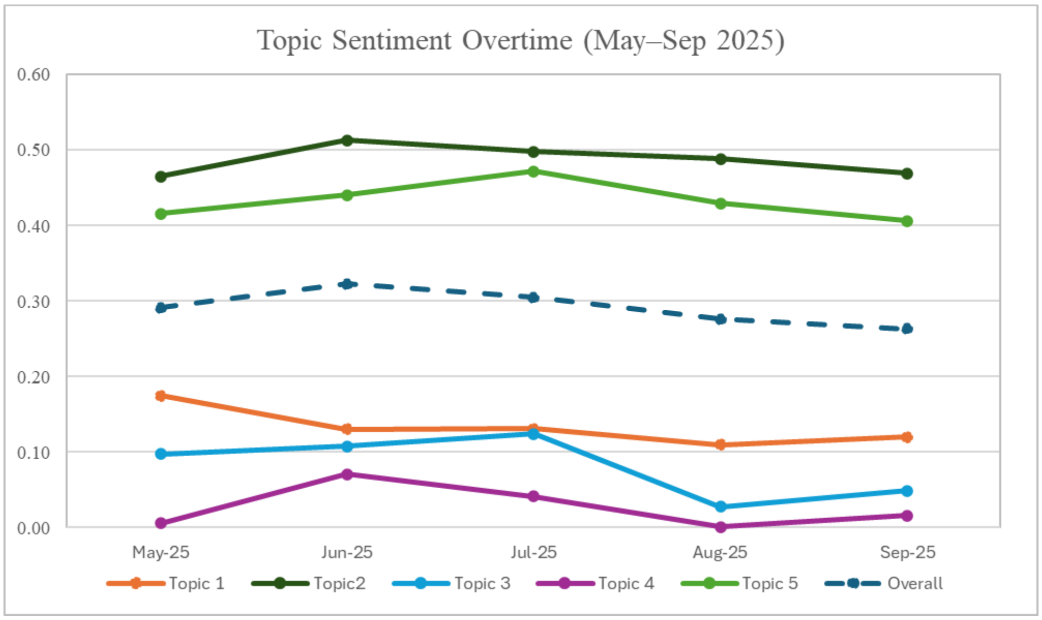

Figure 21 Overall & Topic-Level Sentiment Over Time

Example: In Topic 1, many comments explicitly request fixes, describe problems, or express annoyance, yet users still rate 4–5 stars, showing a gap between emotional expression and quantitative scoring. (table below)

Author	Review	Rating	Compound(Sentiment)
lala khan	On top of all the technical issues (how is picture/video quality STILL this bad on android after DECADES of development???) they're also now sending me notifications for EXTREMELY disturbing content. They only allow me to report individual accounts, but my whole explore page is filled with graphic, disgusting images of rotting flesh, insects burrowing into skin, close ups of oozing wounds, & NO WAY TO TURN IT OFF! I've NEVER clicked ANY content similar to this, theres NO reason I should see it	5	-0.9559
Nthabiseng Nthase	im so sick of the glitching and inappropriate ads Snapchat is definitely buged they need to fix their stuff asp because you	5	-0.9588

	can't expect people to keep your app and use it if it's quite literally rage bait there is bad glitching I can't send snaps or pics sometimes it lags really bad somethings don't save and it will kick you out all together when you ain't even do nothing my phone may lag a little but snap is a new level of lag and rage bait ik multiple people who can say the same NOT FOR KIDS		

Table 5: User Reviews and Ratings

7. Recommendations (Answering the Research Question)

1. **Improve camera reliability and feature support**, especially wide-angle and Android compatibility, as recurring camera issues are a major source of frustration.
2. **Reduce ad intrusiveness and notification overload** by optimizing ad placement, frequency, and relevance to minimize disruption to messaging and story viewing.
3. **Increase transparency and responsiveness in account enforcement**, including clearer reasons for bans/locks and a more reliable recovery workflow.
4. **Strengthen core social features** such as chat, calling, and filters, as these drive positive sentiment and represent Snapchat's strongest value proposition.
5. **Integrate sentiment-aware analytics into product monitoring**, since high ratings frequently mask negative written feedback; topic-level sentiment is a more accurate signal of user experience.

7.1 Future Research Directions

- **Analyze device-level differences** (e.g., Android vs. iOS) to determine whether technical issues cluster by platform.
- **Conduct longitudinal tracking** of topics and sentiment across longer periods or after major updates to identify causal effects.
- **Segment users by rating–sentiment mismatch** to understand which groups rate highly but complain heavily in text.
- **Explore sub-topics within negative themes** (e.g., categorize ad complaints into frequency, relevance, placement).
- **Combine behavioral data (e.g., retention, open rates)** with topic sentiment to identify which frustrations correlate with churn.

8. Summary

This study analyzed 43,624 cleaned Snapchat user comments to uncover key discussion themes and sentiment patterns using topic modeling, lexicon-based sentiment analysis, and visual analytics. Five stable topics emerged - Camera Issues, User Enjoyment, Ad-Related Disruptions, Account Access & Restrictions, and Social Engagement - each revealing distinct user experiences. While social and creative features consistently generate strong positive sentiment, camera reliability problems, intrusive ads, and account-related friction remain major pain points. Topic-level analysis also uncovered a persistent rating–sentiment mismatch, with users often giving 4–5 star ratings despite expressing negative emotions in text. These insights highlight where Snapchat delivers value and where targeted improvements could strengthen user trust, reduce frustration, and enhance overall engagement.

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