# Computational Sentiment Analysis of User Interactions on Live Streaming Platforms Using Artificial Expert Judgment

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Abstract— This study examines user interaction patterns on JKT48 Showroom live streaming using sentiment analysis on 14,857 interactions processed with a Large Language Model. The results show that most interactions are neutral (93.63%) with positive and negative sentiments appearing in smaller proportions. This suggests that user participation is mainly routine and reflects a form of "silent loyalty". The findings highlight the importance of maintaining a stable user experience to support long term engagement.
Keywords—behavioral loyalty, computational social science, neutral sentiment, user participation.

## I. INTRODUCTION

Digital platforms have become an important medium for consumer interaction. One example is Showroom-live.com, which enables real-time communication between performers and audiences and can foster parasocial bonds [1], [2]. Previous studies have also used machine learning approaches to analyze user-generated content, including Vtuber chats interactions [3]. However, most studies focus on transactional aspects while non-transactional engagement has received less attention [4]. In live streaming environments, user participation is not always reflected through transactional activities such as donations or virtual gifting and continuous presence during broadcasts which may still indicate ongoing audience involvement within digital communities. This suggests that engagement in live streaming platforms can also develop through routine and low intensity interaction patterns over time. The rapid growth of digital communication has increased the amount of interaction data generated by online users, making computational approaches such as sentiment analysis increasingly relevant for understanding communication behavior in digital environments. Compared to manual analysis, computational methods allow researchers to process larger datasets more efficiently while still identifying broader interaction patterns in real-time interactions. In addition, neutral interactions are often overlooked because they are considered less emotionally expressive than positive or negative responses. However the dominance of neutral communicatio may indicate stable participation patterns and continuous audience presence within the platform ecosystem. This study aims to examine user interaction patterns by using Large Language Models (LLMs) to support the analysis of interactions data.

## II. METHOD

Through digital observation of 14,857 testimonials, this applies an LLM-based approach to classify interaction data [5], [6]. The classification process was supported by Gemini to categorize user sentiment [7], [8], while phenomenological analysis was used to interpret the results [9]. The system was designed to identify interaction within the digital fandom environment. The overall research workflow, from data collection to analysis, is presented in Figure 1.

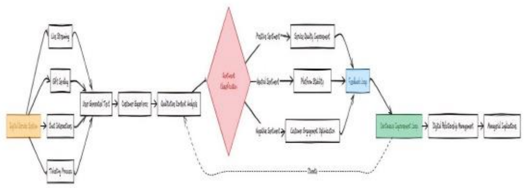

**Figure 1. Diagram research workflow**

Before the analysis, the dataset was preprocessed to improve data quality, including removing system generated content, normalizing informal language and eliminating duplicate entries. After this, step 13,911 valid interactions were retained for sentiment classification. The preprocessing stage was conducted to reduce noise within the interaction dataset and improve the consistency of the classification process. Informal expressions, repetitive messages and automatically generated notifications were filtered to ensure that the analysis focused primarily on user generated communication. This process also helped minimize potential bias caused by duplicated or irrelevant interaction data.After preprocessing, the interaction data were analyzed using an LLM-based sentiment classification approach to identify positive, negative and neutral communication patterns.

The classification results were then interpreted through a phenomenological perspective to better understand how users interact within the live streaming environment. This approach allowed the study to combine computational analysis with contextual interpretation of digital interaction behavior.

## III. RESULTS AND DISCUSSION

### A. RESULT

The implementation of an LLM based classification approach enabled the analysis of 14,857 interaction logs. This approach provides an alternative to manual coding by using classification model [5], [7]. The results, presented in Table 1, show the distribution of sentiment within the JKT48 Showroom dataset.

Before obtaining the final results, the dataset was preprocessed to remove automated system notification and repetitive entries, ensuring that only user generated content was analyzed. A preliminary validation step was also conducted to check the consistency of the classification process.

**Table 1. Sentiment Classification Result**

| Sentiment Category | Number of Reviews | Percentage |
|---|---|---|
| Positive | 499 | 3.36% |
| Neutral | 13,911 | 93.63% |
| Negative | 447 | 3.01% |
| Total | 14,857 | 100% |

The results show that 93.63% (n=13,911) of interactions are classified as neutral. Positive sentiment accounts for (3.36% n=499) while negative sentiment represents (3.01% n=447). These results indicate that neutral interactions dominate the dataset. This distribution suggests that the model is able to distinguish routine communication from more expressive interaction [8], [10]. To examine these patterns further, thematic mapping was conducted (Figure 2) to identify common interaction trends [6].


**Figure 2. Thematic Word Cloud of User Interaction on Showroom**

The word cloud highlights frequency terms such as “Aku”, “Kamu”, “Hari”, “Lagi”, “Udah”, and “Wkwkwk”, which reflect common conversational patterns among users. These patterns are consistent with the high proportion of neutral interactions in the dataset. Previous studies have discussed similar forms of interaction in live streaming environments [11]. In addition, the interaction pattern appears relatively stable across different periods, including high traffic events such as the Sosenkyo campaign [12].

**B. DISCUSSION**

The finding that 93.63% of interactions are neutral suggests the need to reconsider how engagement is interpreted in live streaming environments. In this context, neutral interaction may reflect a form of “silent loyalty”, where users maintain a consistent presence without strong emotional expression. This pattern aligns with the concept of flow, in which continuous and low-intensity interaction supports long-term engagement [9],[12].

Compared to live streaming systems that rely on high-arousal engagement triggers [13], the Showroom environment appears relatively stable. The results indicate that user participation is shaped more by routine interaction than by short-term peaks. While previous research often focuses on highly active users [4], these findings highlight the role of less expressive participants in maintaining overall system stability. In other digital contexts, sentiment distributions tend to be varied with lower neutral proportions reported in prior studies [14], [15]. This difference suggests that interaction patterns in this platform may be more consistent over time.

Another aspect that can be considered is how neutral interactions function as a form of low-effort participation. Users may not always express strong emotions but still choose to remain present in the interaction space. This suggests that engagement is not only reflected through visible activity but also through consistent presence over time. Such behavior indicates that accessibility and ease of interaction play an important role in sustaining user activity on the platform.

In addition, the stability of interaction patterns may reflect user adaptation to the platform environment. Over time, users may develop habitual interaction styles that require minimal effort while maintaining asense of participation. This indicates that engagement is influenced not only by content but also by how the interaction system supports repeated and sustainable use.

From a technical perspective, live streaming platforms differ from algorithm driven social media feeds. In live environments, users share a real-time interaction space. Continuous high-intensity engagement may not be sustainable in this setting. Features that allow flexible and low-effort participation may help reduce user fatigue and support repeated engagement over time

On the methodological side, the use of an LLM based classification approach enables large-scale analysis of user interactions that would be difficult to process manually. Traditional methods may have limitations in capturing informal language or context specific expressions. The results suggest that LLM based approaches can support efficient analysis while still capturing general interaction patterns in large datasets.

Another point that can be considered is how interaction intensity does not always correspond to user commitment. In many digital environments, high levels of visible activity are often interpreted as strong engagement. However, the findings in this study suggest that consistent low-intensity interaction may also indicate a stable form of participation. This highlights the possibility that user commitment can be expressed through continuity rather than frequency or emotional intensity .

In addition, it is possible that neutral interactions serve as a mechanism to maintain social presence without requiring significant cognitive or emotional effort. This type of interaction may also allow users to remain connected while minimizing engagement fatigue. As a result, the platform can sustain long-term participation by supporting interaction patterns that are simple, accessible and repeatable. This also indicates that low-effort participation may play an important role in maintaining user retention within live streaming environments.

The findings of this study can also be viewed from the perspective of interaction sustainability within digital platforms. The dominance of neutral interactions suggests that user participation is not driven solely by expressive or emotionally intense behavior, but also by the ability to maintain a consistent presence over time. This indicates that sustainable engagement may depend on how well a platform supports routine interaction patterns.

In this context, interaction sustainability refers to the capacity of a platform to retain user participation through stable and repeatable forms of engagement. Rather than relying on temporary spikes of activity such as high-intensity or promotional events, the platform may benefit from supporting continuous low-intensity participation. This type of engagement may create a more predictable interaction environment, which can contribute to long-term user retention.

Furthermore, stable interaction patterns may reduce the need for users to constantly generate new or highly expressive content. By allowing users to participate with minimal effort, the platform can lower the barrier to entry and sustain user activity over longer periods. This suggests that simplicity and accessibility in interaction design may play a significant role in maintaining engagement within live streaming environments.

From a broader analytical perspective, the findings of this study highlight the importance of interaction structure in shaping user behavior within live streaming platforms. Rather than being driven primarily by individual emotional expression, user participation appears to be influenced by the overall design of the interaction environment. This suggests that user behavior is not only a result of individual interaction, but also a response to how interaction systems are organized and experienced.

In addition, the dominance of neutral interactions may indicate that users are moreresponsive to interaction accessibility than to stimulation intensity. When participation does not require significant effort or emotional investment, users may be more likely to maintain consistent involvement over time. This highlights the role of interaction design in lowering participation barriers and supporting sustainable engagement patterns.

Furthermore, these findings suggest that the effectiveness of a platform may depend on its ability to facilitate stable and predictable interaction flows. Instead of focusing solely on increasing user activity levels, the platform may benefit from creating environments that support continuity and ease of participation. This perspective reinforces the idea that long-term engagement is closely related to interaction stability rather than momentary intensity.

This research has several limitations that should be considered when interpreting the findings. First, the dataset is limited to a single platform (Showroom) and a specific fandom (JKT48), which may affect the generalizability of the results to other live streaming environments or cultural contexts. Different platforms may exhibit distinct interaction patterns depending on their features and user characteristics.

Second, the analysis focuses only on textual interaction data derived from user chat activity within a specific observation period. Other forms of interaction, such as virtual gifting behavior and broader user activity metrics, are not included in this study. Including these aspects may provide a more comprehensive understanding of engagement in future research.

Third, while the use of an LLM based classification approach enables large-scale analysis, it may still have limitations in interpreting highly contextual or informal expressions, especially those influenced by local language and fandom specific communication styles.

Future research may extend this work by comparing multiple platforms or fandom communities to identify whether similar interaction patterns are observed. In addition, combining LLM based approaches with manual validation may improve classification reliability. Further studies may also explore multimodal or behavioral data to provide a more comprehensive understanding of user interaction in live streaming environments.

## IV. CONCLUSION

This study examines user interaction patterns on the JKT48 platform using an LLM based sentiment analysis approach. The findings show that most interactions are neutral, indicating that user participation is largely driven by routine and continuous presence rather than strong emotional expression. This pattern reflects a form of “silent loyalty”, where users remain engaged through consistent but low-intensity interaction over time.

The presence of this interaction suggests that engagement in live streaming environments may not always be reflected through highly visible or expressive behavior. Instead, consistent participation, even simple forms such as short messages or repeated presence, may represent an important aspect of user involvement. This indicates that engagement can take multiple forms, including those that are less visible but still contribute to the overall activity of the platform.

From a system perspective, these findings highlight the importance of maintaining a stable and reliable platform environment. Features that support smooth interaction, low disruption and accessibility may help users sustain their participation over time. Rather than focusing only on short-term engagement strategies, platform design may benefit from supporting everyday interaction patterns that encourage users to return regularly.

In addition, the results suggest that the relationship between users and content creators may be influenced by routine interaction rather than occasional high-intensity engagement. This may indicate that long-term participation is shaped by familiarity and consistency, which can contribute to the continuity of interaction within the platform environment.

This study also demonstrates the potential of LLM based approaches in analyzing large-scale user interaction data. By enabling efficient processing of textual data, such as user interaction data this approach can support the identification of general interaction patterns that may not be easily observed through manual analysis. However, these methods should be used with consideration of their limitations, particularly in interpreting context specific or informal expression.

Overall, this study contributes to a better understanding of user behavior in live streaming environments by highlighting the role of consistent and low-intensity interaction. Future research may explore similar patterns across different platforms, incorporate additional forms of data or examine how this interaction patterns evolve over time. Understanding these dynamics may provide a more comprehensive perspective on digital engagement in evolving online ecosystems.

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