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Sentiment Analysis of User Comments on Vidio.com Digital Streaming Platform in Indonesia

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Abstract

The development of digital streaming platforms has transformed the way people access entertainment, including in Indonesia, making sentiment analysis of user experience crucial for evaluating service quality. This study aims to analyze Vidio.com user sentiment based on 173,868 comments during April 2026 and identify the distribution of sentiment and key factors influencing user perceptions. The method used is lexicon-based sentiment analysis with data preprocessing and classification of positive, negative, and neutral polarities using a computational approach on large-scale text data. The results show that sentiment is dominated by negative (52.3%), followed by neutral (44.3%) and positive (3.4%), with the main issues stemming from ad interruptions and technical issues such as buffering and content playback. These findings indicate that user experience is still influenced by monetization strategies and infrastructure quality, particularly regarding excessive advertising. In conclusion, improving service quality and optimizing advertising strategies have important implications for platform development to increase user satisfaction and engagement. The implication is that the results of this study can be used as a basis for data-based decision-making in improving user experience through improving streaming systems, reducing ad interruptions, and strengthening continuous sentiment evaluation to support business strategies that are more responsive to user needs.

Keywords

Digital Streaming, Lexicon-Based Method, Sentiment Analysis, User-Generated Content, Vidio.Com.

1. Introduction

The rapid advancement of digital technology has fundamentally transformed the way people access and consume entertainment. One of the most significant developments has been the emergence of digital streaming platforms, which enable users to enjoy content anytime and anywhere through various internet-connected devices. In Indonesia, the streaming industry has experienced remarkable growth, driven by increasing internet penetration, widespread smartphone adoption, and changing media consumption patterns. This development has intensified competition among both local and international streaming providers, encouraging companies to continuously improve content quality, service performance, and user experience. In such a highly competitive digital environment, understanding customer perceptions and satisfaction has become essential for maintaining user loyalty and sustaining competitive advantage (Cortis & Davis, 2020).

Among the major streaming platforms operating in Indonesia, Vidio.com has established itself as a prominent provider of diverse entertainment services, including live sports broadcasts, television programs, films, drama series, and exclusive digital content. Beyond content consumption, user interaction on the platform is also reflected through the comment feature, which allows audiences to express opinions, experiences, criticisms, and appreciation regarding the services provided. These comments represent a valuable form of user-generated content that offers direct insights into customer perceptions and experiences (Fernandez, 2021). From a business perspective, online user feedback serves as an important source of information for evaluating service quality, identifying customer expectations, and understanding audience engagement in digital environments (Cortis & Davis, 2020; Khairifa & Mardhiyah, 2023).

The increasing volume of user-generated comments has created significant challenges for organizations seeking to understand customer opinions effectively. Manual analysis of large-scale textual data is often impractical, time-consuming, and susceptible to human bias. Consequently, sentiment analysis, also known as opinion mining, has emerged as a widely adopted computational approach for automatically identifying, extracting, and classifying opinions expressed in textual data (Trupthi et al., 2017). By employing techniques from Natural Language Processing (NLP) and machine learning, sentiment analysis enables researchers and organizations to categorize textual content into positive, negative, or neutral sentiments. Previous studies have demonstrated that sentiment analysis can provide valuable insights for customer relationship management, service evaluation, and data-driven decision-making processes (Kobs et al., 2020).

The motivation for this study stems from the substantial volume of user comments generated on Vidio.com during April 2026, totaling 173,868 comments. This figure reflects a high level of user engagement while simultaneously creating a large-scale dataset containing valuable information about customer experiences and perceptions. However, the sheer volume of comments makes traditional manual analysis inefficient and impractical. As a result, automated sentiment analysis becomes a relevant and effective solution for identifying public opinion patterns, detecting potential service issues, and recognizing aspects of the platform that are positively received by users. Supeli and Setiaji (2023), as well as Permana (2024), argued that the ability to process and interpret large-scale textual data can provide organizations with actionable insights for improving service quality and enhancing customer satisfaction.

Despite the growing body of literature on sentiment analysis, most previous studies have focused on social media platforms such as X (formerly Twitter), Instagram, YouTube, and online discussion forums. Research specifically examining user sentiment within Indonesian digital streaming platforms remains relatively

limited. Furthermore, many existing studies utilize datasets of considerably smaller size, which may not fully capture the complexity and diversity of user opinions. Therefore, this study addresses this gap by conducting a large-scale sentiment analysis of 173,868 user comments collected from Vidio.com during April 2026. The novelty of this research lies in its focus on a leading Indonesian streaming platform and the utilization of a substantially larger dataset, providing a more comprehensive representation of customer perceptions in the digital streaming industry.

The objective of this study is to analyze user sentiment toward Vidio.com based on comments posted during April 2026, identify the distribution of positive, negative, and neutral sentiments, and provide a comprehensive understanding of customer perceptions regarding the platform's services. Through this analysis, the study seeks to generate meaningful insights into user experiences and expectations within the context of digital streaming services. This research contributes to both academic and practical domains. This study contributes to the literature by extending the application of sentiment analysis to Indonesia's underexplored digital streaming platform context while providing practical insights to support Vidio.com in enhancing service quality, user experience, customer engagement, and strategic decision-making based on user feedback.

2. Literature Review

2.1. Sentiment Analysis

Sentiment analysis, also referred to as opinion mining, is a prominent branch of Natural Language Processing (NLP) that focuses on the identification, extraction, and classification of opinions expressed in textual data. According to Liu and Chen (2015), sentiment analysis is the computational study of people's opinions, sentiments, evaluations, emotions, and attitudes toward various entities, including products, services, organizations, individuals, and specific issues. With the rapid growth of user-generated textual data on social media platforms, online forums, and digital services, sentiment analysis has become an increasingly important tool for understanding public perceptions in an efficient and systematic manner. This approach enables researchers and organizations to identify opinion trends and evaluate user responses more effectively than traditional manual analysis, which is often time-consuming and resource-intensive (Waluyan & Hartomo, 2022; Aji, 2025).

Sentiment analysis can be conducted at three different levels: document-level, sentence-level, and aspect-level. The document-level approach classifies an entire text according to its overall sentiment orientation, whereas the sentence-level approach examines the sentiment expressed within individual sentences. In contrast, the aspect-level approach focuses on identifying sentiments toward specific attributes or features of an entity. The present study adopts the document-level approach because each user comment is treated as a single unit of analysis. Previous studies have commonly categorized sentiment into three primary classes: positive, negative, and neutral. Positive sentiment reflects satisfaction, appreciation, or favorable evaluations, while negative sentiment indicates dissatisfaction, criticism, or unfavorable opinions (Duan et al., 2013). Neutral sentiment, on the other hand, represents informational statements that do not convey a strong emotional orientation. Xu et al. (2019) and Fernandez (2021) stated that these three categories have been widely employed in studies examining customer perceptions of products and services, as they provide a comprehensive representation of user opinions and experiences.

2.2. Streaming Platforms and User-Generated Content

Video streaming platforms are digital services that allow users to access audiovisual content through the Internet, either via live streaming or on-demand

services. The rapid growth of Internet access and digital technology has significantly expanded the streaming industry worldwide, including in Indonesia. According to Moreo et al. (2012), streaming platforms have transformed media consumption patterns by providing audiences with greater flexibility and control over the content they watch. In Indonesia, platforms such as Vidio.com, Netflix, Disney+, and WeTV have become increasingly popular as consumers shift from traditional broadcasting to digital entertainment services. Beyond content delivery, these platforms also encourage user participation through interactive features that facilitate communication and engagement among audiences.

A key form of interaction on streaming platforms is User-Generated Content (UGC), which includes comments, ratings, reviews, and other user contributions. According to Alrumaih et al. (2020) and Li et al. (2023), UGC refers to content created and published voluntarily by users through online platforms. User comments are particularly valuable because they provide direct insights into audience experiences and perceptions. However, comments on streaming platforms present unique analytical challenges. They are often short, informal, and characterized by slang, abbreviations, spelling errors, and emotional expressions. In the Indonesian context, comments may also involve code-switching between Bahasa Indonesia and regional languages, such as Javanese or Sundanese, while containing references specific to the content being viewed. These characteristics make sentiment identification and text analysis more complex than in conventional product reviews (Cui et al., 2013; Gitari et al., 2015).

2.3. Lexicon-Based Method

The lexicon-based method is a classical approach in sentiment analysis that determines sentiment polarity by matching words in a text with a predefined sentiment lexicon. Each word in the lexicon is assigned a sentiment label or score, typically positive or negative, and the overall sentiment of a text is computed based on the frequency and weighting of the matched words. According to Taboada et al. (2011), lexicon-based sentiment analysis relies on sentiment dictionaries that encode semantic orientation and strength of words to estimate the overall polarity of a document. Similarly, Liu and Chen (2015) emphasize that this approach is widely used due to its simplicity and interpretability, as the classification results can be directly traced back to the contributing words in the text.

Despite its advantages, the lexicon-based approach has several limitations. Its performance is highly dependent on the quality and coverage of the sentiment lexicon used, and it often struggles to capture contextual meaning such as sarcasm, negation, and domain-specific expressions (Nandwani & Verma, 2021). In the context of informal Indonesian text, such as user comments on Vidio.com, these challenges become more pronounced due to the presence of slang, abbreviations, and non-standard language. Therefore, adapting the sentiment lexicon to the specific linguistic characteristics of the dataset is essential. As noted by Wankhade et al. (2022) and Sharma et al. (2025), domain adaptation of sentiment resources plays a crucial role in improving classification performance. In this study, the lexicon is customized to include informal expressions, common abbreviations ("*gak*" for "*tidak*"), and domain-specific terms frequently used in streaming platform discussions.

3. Methods

This study employs a quantitative descriptive research design combined with a computational text analysis approach. The quantitative descriptive method is selected because the primary objective of this study is to describe and measure sentiment distribution numerically based on the available dataset. In addition, a computational approach is applied to enable large-scale data processing, particularly

since the dataset consists of 173,868 user comments that cannot be feasibly analyzed manually. This approach ensures that the analysis is systematic, scalable, and reproducible.

The data used in this study is secondary data obtained from the internal system of Vidio.com. The dataset consists of user comments collected from live chat features and content comment sections on the platform. The data covers the period from April 1, 2026, to April 30, 2026, resulting in a total of 173,868 records with an average of approximately 5,795 comments per day. Each record contains several attributes, including the timestamp in Western Indonesia Time (*Waktu Indonesia Barat*/WIB), anonymized user identification, content identifier, and content type, and automatically generated topic classifications provided by the platform's internal system. The main variable of interest in this study is the textual content of user comments.

Sentiment analysis is conducted using a lexicon-based approach with an Indonesian sentiment dictionary specifically developed for the streaming platform context. The analysis process begins with data preprocessing, which includes converting text to lowercase and removing non-alphanumeric characters. After preprocessing, sentiment classification is performed by matching words in the text with entries in the sentiment lexicon to calculate the frequency of positive and negative terms. A comment is classified as positive if positive words dominate, negative if negative words are more frequent, and neutral if both are equal or no sentiment words are detected. Comments with fewer than three characters are automatically labeled as neutral to ensure data quality.

This study also utilizes pre-existing topic categorization provided by Vidio.com's internal machine learning system, which includes 17 main categories and more than 30 subcategories. These categories are used as an additional analytical dimension to examine sentiment distribution across different types of user issues and discussions. The data processing is conducted using Python 3.12, with pandas used for data manipulation and openpyxl for generating structured output reports in Excel format. All analyses are performed in a cloud computing environment to ensure efficient processing of large-scale data, and the workflow is designed to be fully reproducible.

4. Results

4.1. Overall Sentiment Distribution

The dataset analyzed in this study consists of 173,868 user comments from Vidio.com, collected over a 30-day period from April 1 to April 30, 2026. The average number of comments per day was 5,795, with a relatively consistent distribution throughout the month. The data cover various types of content consumed by users, including live sports streaming, soap operas, films, and other entertainment programs. The comments vary significantly in length, ranging from very short expressions of 1–3 words to longer texts containing detailed descriptions of complaints or praise. The distribution of comments across topics indicates that Ads Issue dominates the dataset with 46.5% of total comments, followed by Others (29.1%) and Content Issue (13.7%). This finding suggests that advertising-related experiences are the most frequently discussed aspect among users.

Table 1. Sentiment Distribution of Video.com User Comments

Sentiment Category	Number of Comments	Percentage
Positive	5,884	3.4%
Negative	90,985	52.3%
Neutral	76,999	44.3%
Total	173,868	100%

Table 1 presents the overall distribution of sentiment in Vidio.com user comments during April 2026. The results show that of the 173,868 total comments, the majority were classified as negative (52.3%), followed by neutral (44.3%), and only a small portion fell into the positive category (3.4%). This distribution indicates a predominance of negative sentiment in user comments on the platform. A similar pattern is often found in sentiment analysis research, where negative expressions tend to be more dominant in online discussions because users are more active in expressing dissatisfaction than satisfaction (Yadav & Vishwakarma, 2020; Cortis & Davis, 2021). The substantial proportion of neutral comments also reflects the characteristics of user comments, which are often brief, descriptive, or context-dependent, thus not indicating a clear polarity of sentiment.

The predominance of negative sentiment does not necessarily mean that the majority of users are dissatisfied with the platform. As explained in previous research, user-generated content is often influenced by negativity bias, which is the tendency for individuals to be more inclined to report negative experiences than positive ones (Ranjan et al., 2024; Khekare et al., 2025). Therefore, the negative proportion of 52.3% is more accurately understood as an indicator of a high level of responsiveness to problematic experiences, rather than an absolute measure of overall user dissatisfaction. Meanwhile, neutral comments (44.3%) generally consisted of brief reactions, contextual statements, or expressions lacking sentimental words detectable by lexicon-based approaches. The relatively small proportion of positive comments (3.4%) suggests that users are less likely to explicitly express satisfaction in the comments section than to express complaints or neutral responses to content.

4.2. Sentiment Analysis by Topic

Further analysis was performed by breaking down the sentiment distribution based on topics categorized by Vidio.com's internal system. The results are presented in Table 2.

Table 2. Sentiment Distribution by Topic

Topic	Positive	Negative	Neutral	Total	Negative (%)
Ads Issue	225	76,369	4,206	80,800	94.5%
Others	3,262	5,287	42,092	50,641	10.4%
Content Issue	1,553	6,352	15,944	23,849	26.6%
Homepage & Recommendation Issue	214	586	8,841	9,641	6.1%
Playback Error	247	1,293	1,852	3,392	38.1%
General Subscription	114	508	1,483	2,105	24.1%
Payment Quality	62	134	525	721	18.6%
Account Issue	53	98	487	638	15.4%
Search Issue	30	43	322	395	10.9%
Watchpage / CPP	33	40	306	379	10.6%
Paywall Experience	20	44	261	325	13.5%
Shorts & Coins	17	33	136	186	17.7%
Content Decision Issue	26	30	123	179	16.8%
Preference & Explicit Feedback	4	18	140	162	11.1%
Cover / Poster Issue	2	19	80	101	18.8%
Category Issue	6	9	65	80	11.2%
Ads Quality	0	2	0	2	100.0%

Table 2 shows the distribution of Vidio.com user sentiment based on various problem topics raised in comments. In general, the problems are not evenly

distributed, but rather concentrated in certain topics, with a very high prevalence of negative sentiment. This indicates that the user experience is significantly influenced by specific aspects of the platform, particularly those related to advertising and core service quality (Sykora et al., 2022).

First, the ad issue was the topic with the largest comment volume and the highest level of negative sentiment, accounting for 94.5% of the 80,800 comments. Almost all comments in this category were negative (76,369 comments), indicating strong dissatisfaction with the advertising experience on the Vidio.com platform. This finding is an important indicator that monetization through advertising has the potential to disrupt the user experience and requires urgent improvement.

Second, the "others" topic had a large number of comments (50,641), but a relatively low level of negative sentiment, at 10.4%. Most comments in this category tended to be emotional reactions to content, such as joy, surprise, or sadness, that were not directly related to service quality. Additionally, content issues recorded 23,849 comments, with 26.6% negative sentiment, largely driven by complaints about content availability, video quality, and subtitles. Meanwhile, playback errors, despite having a smaller volume (3,392 comments), remain a concern because they directly relate to the user's primary technical experience in accessing content without interruption.

4.3. Sentiment Analysis by Sub-Category

To gain a more granular understanding, the analysis was conducted at the topic subcategory level. The ten subcategories with the highest volume are presented in Table 3.

Table 3. Top 10 Sub-Category Topics Based on Comment Volume

No	Sub-Category Topic	Total Comments	Negative (%)
1	Too many ads	62,196	94.5%
2	General comment about content	50,638	10.4%
3	Ad's duration too long	15,872	96.0%
4	Buffering issue	11,710	26.4%
5	Time spent going back and forth searching for content to watch	8,352	5.5%
6	Other content-related issues	3,753	22.2%
7	Unable to play content	3,117	40.7%
8	Content not available on Vidio	2,852	16.8%
9	Ads stuck / not playable	2,729	86.4%
10	Audio issue	1,934	14.1%

Table 3 shows ten main subcategories based on the volume of Vidio.com user comments, indicating that the most dominant issues relate to the ad experience and the platform's technical performance. The subcategory with the highest volume is dominated by complaints about ads, which also have a very high level of negative sentiment. This indicates that monetization is the primary factor influencing user satisfaction (Saura et al., 2019).

The subcategory "Too many ads" was the most dominant, with 62,196 comments and a negative sentiment level of 94.5%. This complaint indicates that users feel the ad frequency is too high, significantly disrupting their viewing experience. Furthermore, the subcategory "Ad duration too long" corroborates these findings with 15,872 comments and 96.0% negative sentiment, indicating that not only the number of ads is a problem, but also their duration, which users consider excessive. The combination of these two issues creates a less-than-optimal viewing experience, especially for non-premium users.

On the technical side, the "Buffering issue" subcategory recorded 11,710 comments, with 26.4% negative sentiment, indicating disruptions to streaming stability that directly impact the user experience. Meanwhile, "general comments

about content" had a high volume (50,638 comments) but a low level of negativity (10.4%), indicating that most users responded neutrally or emotionally to the content, rather than criticizing its quality. These findings suggest that Vidio.com's main issues lie not solely with content quality, but more predominantly with the ad experience and the platform's technical performance.

4.4. Daily Sentiment Trends

Sentiment trend analysis was conducted to understand how user sentiment changed from day to day during April 2026. Table 4 presents a summary of the daily trend data.

Table 4. Daily Trend Data

Date	Positive	Negative	Neutral	Total
2026-04-01	104	1,261	1,349	2,714
2026-04-02	166	2,646	3,411	6,223
2026-04-03	131	1,281	2,182	3,594
2026-04-04	130	1,006	1,350	2,486
2026-04-05	250	3,140	3,322	6,712
2026-04-06	231	2,760	3,432	6,423
2026-04-07	325	8,173	6,887	15,385
2026-04-08	213	2,857	3,554	6,624
2026-04-09	245	6,326	3,706	10,277
2026-04-10	148	6,842	2,994	9,984

Table 4 shows the daily trend in Vidio.com user comment sentiment during the period April 1–10, 2026, which demonstrates significant fluctuations in user activity. In general, negative sentiment dominated each day compared to positive sentiment, indicating that user perceptions of the platform tended to remain consistently dissatisfied. Spikes in comment volume were also observed on certain dates, suggesting the possibility of specific triggers on those days (Zhang et al., 2016).

Peak activity occurred on April 7, 2026, with a total of 15,385 comments, of which negative sentiment accounted for 8,173. On the same day, all sentiment categories increased significantly, indicating a major event or disruption that triggered a widespread user reaction. A high trend was also observed on April 9 and 10, with a total of 10,277 and 9,984 comments, respectively, again dominated by negative sentiment. This pattern suggests that user dissatisfaction is not incidental but occurs repeatedly over several consecutive days.

Although there was an increase in positive and neutral sentiment on certain days, the numbers still failed to outweigh the dominance of negative sentiment. This strengthens the indication that the Vidio.com user experience during the observation period was still dominated by issues that triggered dissatisfaction, thus requiring further attention, especially on aspects of service stability and overall user experience.

5. Discussion

The findings of this study indicate that user discourse on Vidio.com is predominantly characterized by negative sentiment across overall distribution, topic-level analysis, and sub-category breakdowns. This pattern is consistent with Luca (2015) and Rasool and Pathania (2021), the concept of negativity bias, which suggests that individuals are more likely to express and report negative experiences than positive ones in digital environments. Rather than simply reflecting low user satisfaction, this dominance of negative sentiment should be interpreted as a higher level of responsiveness toward problematic or disruptive experiences. In other words, users tend to be more vocal when encountering issues, while positive

experiences are less frequently articulated in comment sections (Cortis & Davis, 2021).

At the topical level, the prominence of advertising-related complaints highlights the central role of monetization strategies in shaping user experience. Prior research by Duan et al. (2013) in user experience design suggests that excessive or intrusive advertisements can significantly reduce perceived usability and increase cognitive burden during content consumption. The strong concentration of negative sentiment within Ads Issue, therefore, indicates a structural tension between revenue generation and user comfort. In streaming platforms, where uninterrupted content consumption is a key value proposition, advertising intensity becomes a critical determinant of perceived service quality.

Technical issues such as buffering and playback errors further reinforce the importance of system reliability in shaping user satisfaction. This aligns with the Technology Acceptance Model, which emphasizes that perceived ease of use and system performance are fundamental determinants of user acceptance of technology. When technical disruptions occur repeatedly, users are likely to generalize these negative experiences to the platform as a whole, even if content quality remains high. According to Komarudin et al. (2023), system instability can significantly undermine overall perceived service quality because users evaluate digital platforms based on seamless functionality as much as content value.

At a more granular level, the dominance of complaints related to ad frequency and duration highlights how interruptions in content flow directly affect user engagement. This is consistent with findings by Duan et al. (2013), the concept of flow experience, which emphasizes the importance of uninterrupted and immersive interaction in sustaining user engagement. When advertising disrupts this flow, users experience a break in immersion that reduces satisfaction and increases frustration. The high concentration of negative sentiment in these sub-categories suggests a misalignment between monetization strategy and the preservation of user engagement quality.

The relatively high proportion of neutral comments and the low share of positive sentiment suggest that users are less inclined to explicitly express satisfaction compared to dissatisfaction. This observation aligns with findings by Liu and Chen (2015) in social media sentiment research, which show that positive experiences are often underreported in online environments. Platform performance should not only be evaluated based on the absence of complaints but also on its ability to encourage and sustain positive user expression. These results indicate that improving user experience alone may not be sufficient; fostering positive emotional engagement is equally important for achieving a balanced sentiment distribution over time.

6. Conclusion

Based on an analysis of 173,868 Vidio.com user comments from April 2026, user sentiment was found to be dominated by negative sentiment (52.3%), followed by neutral (44.3%) and positive (3.4%). This finding indicates structural issues in the user experience, particularly related to the dominance of complaints about ad issues, which accounted for 46.5% of the total comments, with a very high level of negative sentiment (94.5%). Furthermore, technical issues such as buffering and content playback failures also emerged as significant factors impacting the user experience. Nevertheless, users still generally considered content quality relatively good, as evidenced by the low level of negative sentiment in the general content-related comments category. Implications are that improving the user experience requires a focus on reforming advertising strategies and strengthening technical infrastructure to avoid disrupting content consumption.

However, this study has several limitations. The analysis was conducted solely on comment data for a one-month period, thus not fully reflecting long-term

dynamics. Furthermore, a classification-based sentiment analysis approach does not always perfectly capture the context of sarcasm or the nuances of users' informal language. Therefore, future research is recommended to use a longer observation period and combine machine learning-based methods with qualitative analysis to improve the accuracy of sentiment interpretation. Future research could also explore the relationship between platform policy changes and longitudinal fluctuations in user sentiment, including the development of a real-time sentiment monitoring system to support more responsive, data-driven decision-making.

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