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What Do Viewers Talk About? Sentiment and Topic Analysis of Audience Comments on a Samsung Galaxy S26 Review on YouTube

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ABSTRACT
The rapid growth of digital media has positioned YouTube as a key platform for consumer information seeking, particularly through smartphone review content that shapes purchasing decisions. This study examines audience sentiment and identifies dominant discussion topics within comments on a YouTube review video of the Samsung Galaxy S26 Series. A quantitative descriptive approach was employed using text mining techniques, with data collected via web scraping yielding a dataset of 1,001 comments. The analysis comprised text preprocessing, lexicon-based sentiment analysis using the Indonesian Sentiment Lexicon (InSet), and topic modeling using Latent Dirichlet Allocation (LDA). The results indicate that positive sentiment dominates the discussion, accounting for 665 comments (66.4%), while 336 comments (33.6%) reflect negative sentiment. Positive comments cluster around themes of feature innovation, design appreciation, and favorable product evaluations, while also reflecting active audience engagement through content requests directed at the creator. Negative comments are primarily driven by concerns over screen reliability issues, particularly the green line problem associated with previous Samsung Galaxy devices. These findings highlight the value of YouTube comment analysis as a source of consumer intelligence, offering practical insights for digital marketing practitioners in managing brand perception and communication strategies during new product launch phases.

***Keyword**: Sentiment Analysis, Topic Modeling, Youtube Comments, Smartphone Review, Audience Perception.*

1. INTRODUCTION

The advancement of digital technology has significantly transformed consumer behavior patterns in the contemporary business landscape. Within the perspective of Digital Consumer Behavior, consumers increasingly depend on digital platforms to search for information, evaluate products, interact with brands, and share consumption experiences before making purchasing decisions (Kotler & Keller, 2022). This transformation has shifted the role of social media from merely communication platforms into strategic channels for customer engagement and electronic Word-of-Mouth (eWOM), where user-generated content and online interactions substantially influence consumer perception and purchase intention (Gupta, 2023). In the digital business era, audience engagement within online platforms has therefore become an important indicator for understanding market response, consumer trust, and brand communication effectiveness (Roberts et al., 2025).

The proliferation of digital media has fundamentally reshaped how consumers seek and process information prior to making purchasing decisions, particularly within the technology product category (Sahitha, 2025). Among the various platforms utilized for this purpose, YouTube has emerged as a prominent channel through which consumers access product references via review content, especially in the smartphone segment (Emmendoerfer, 2024). Such review content not only conveys technical specifications but also generates audience discourse through comment sections, which collectively reflect viewers' perceptions, experiences, and evaluations of the products under discussion (Toussaint et al., 2022).

One review video that garnered considerable audience attention is a publication by the GadgetIn channel covering the Samsung Galaxy S26 Series. Launched in February 2026 at a price range spanning from approximately IDR 16.49 million for the standard variant to IDR 31.99 million for the flagship model, the device attracted substantial public interest (Samsung Electronics Indonesia, 2026). The review video accumulated over 1,248,618 views, underscoring the high level of audience engagement with premium smartphone review content. Furthermore, GadgetIn is widely recognized as one of Indonesia's most influential technology review channels, with approximately 14 million subscribers and more than 3.6 billion cumulative video views on YouTube as of 2026, positioning the channel as one of the largest technology-focused YouTube creators in Indonesia (Social Blade, 2026). In Indonesia's highly competitive smartphone market, audience sentiment emerging during the early post-launch period carries strategic importance for technology vendors, as initial public perception may rapidly influence electronic Word-of-Mouth (eWOM), brand image, and consumer purchase intention (Gani et al., 2025). As consumers increasingly rely on technology reviewers and online discussions prior to making purchasing decisions, audience interactions within GadgetIn videos may therefore reflect broader patterns of digital consumer perception and engagement behavior in Indonesia. Beyond its viewership figures, the comment section of the video contains a diverse array of audience responses, ranging from appreciation of the device's features to reservations regarding its potential shortcomings (Kadel, 2023). This diversity of responses positions the comment section as a compelling data source for examining audience perception of the reviewed product (Shah & Parekh, 2023).

The analysis of user-generated comments on digital platforms holds considerable significance in capturing public sentiment toward a given product (Sri et al., 2024). Sentiment analysis represents one of the most widely adopted approaches for classifying user opinion tendencies into positive or negative orientations (Amin et al., 2026). Complementarily, topic modeling enables the extraction of dominant themes embedded within user commentary

(Häglund & Björklund, 2025). The integration of these two analytical approaches affords researchers a more comprehensive understanding of audience discussion patterns and product perception within digital environments (Laureate et al., 2023).

A body of prior research has drawn upon sentiment analysis of YouTube comments to examine user opinions across various product and service categories, including consumer technology (Lee & T. N. Nguyen, 2023). Nevertheless, scholarly inquiry specifically addressing audience responses to newly launched smartphone products in the Indonesian digital market remains limited, particularly during the early post-launch period when public perception is rapidly formed (Chan et al., 2025). Existing studies have predominantly utilized machine learning classification techniques or generalized sentiment lexicons, while limited attention has been directed toward Indonesian-language sentiment analysis using the Indonesian Sentiment Lexicon (InSet) approach (Okta et al., 2025). This limitation is important because online discourse in Indonesian frequently contains contextual expressions, informal vocabulary, slang, and local linguistic nuances that may not be adequately captured by non-Indonesian or generalized lexicon frameworks. Consequently, the application of the InSet lexicon in this study provides contextual relevance for capturing sentiment tendencies within Indonesian digital communication environments, particularly in audience discussions surrounding newly launched technology products on YouTube (Sally, 2022).

Despite the growing body of research on sentiment analysis of YouTube comments, limited studies have specifically examined audience discourse surrounding newly launched smartphone products during the early post-launch period. Against this backdrop, the present study aims to examine audience perception of smartphone review content on YouTube through the application of lexicon-based sentiment analysis and topic modeling using the Latent Dirichlet Allocation (LDA) method. Specifically, the study seeks to identify prevailing sentiment tendencies and uncover dominant thematic patterns within audience discourse on the Samsung Galaxy S26 Series review video, thereby offering contributions to both the scholarly literature on digital consumer behavior and the practical domain of digital marketing communication.

2. METHODOLOGY

This study employs a quantitative descriptive approach utilizing text mining methods to analyze sentiment and audience discussion patterns derived from user comments on a YouTube smartphone review video. Data were collected from a review video of the Samsung Galaxy S26 Series published by the GadgetIn channel, selected on the basis that it ranks among the largest technology review channels in Indonesia with 13.9 million subscribers, while the video has accumulated over 1,248,618 views. Data collection was conducted through web scraping utilizing the youtube-comment-downloader Python library within the Google Colaboratory environment, yielding a total of 1,001 comments as the research dataset. The overall research procedure is illustrated in Figure 1.

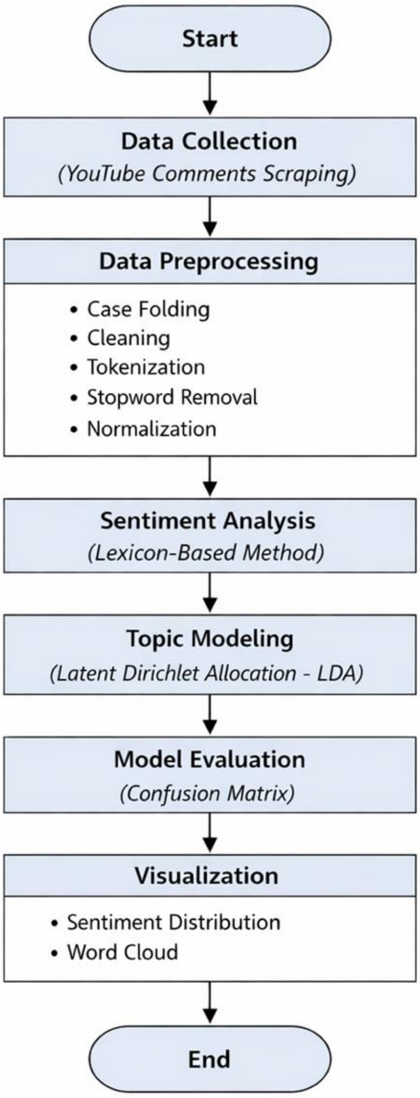

Figure 1. Research Procedure Flowchart

Prior to analysis, the comment text underwent a preprocessing stage comprising case folding, cleaning, tokenization, stopword removal, and normalization to remove irrelevant elements and standardize the text for analytical purposes (Jurafsky & Martin, 2025). The normalization process was conducted to standardize informal Indonesian expressions, abbreviations, and slang words frequently found in YouTube comments into their corresponding standard Indonesian forms. A custom normalization dictionary was developed manually by adapting commonly used Indonesian internet slang and technology-related expressions identified during preliminary data inspection. For example, terms such as “samsul” were normalized to “Samsung”, while expressions such as “udah po” were converted into their formal equivalents. This manual normalization process was complemented by the utilization of Indonesian natural language preprocessing libraries to ensure greater consistency in text standardization across the dataset (van der Veen & Bleich, 2025). Sentiment classification was subsequently performed using a lexicon-based approach drawing upon the Indonesian Sentiment Lexicon (InSet) (Rizka and Fatah, 2025). This approach was selected over supervised machine learning methods on the grounds that it does not require labeled training data, offers greater linguistic transparency, and is particularly suited for analyzing Indonesian-language comments where annotated sentiment datasets remain limited (Asri et al., 2025). Each comment was assigned a sentiment score by aggregating the polarity values of identified words, and subsequently classified as either positive or negative sentiment (Zhang & others, 2024). Topic modeling was then performed using the Latent Dirichlet Allocation (LDA) method to extract latent topics based on word distribution patterns within the comment text, with analysis conducted separately for each sentiment group to yield a more granular understanding of discussion themes (Wang et al., 2022). The number of topics was determined through exploratory testing to obtain the most interpretable set of keywords representing audience discussion themes. Model evaluation was carried out using accuracy, precision, recall, and F1-score metrics supported by a confusion matrix. To evaluate classification performance, a subset of 201 comments was manually annotated to serve as ground truth data. The labeling process was conducted through manual sentiment assessment by the researchers based on the contextual meaning of each comment, categorizing them into positive or negative sentiment classes (Osmani & Mohasefi, 2022). This annotated dataset was subsequently compared with the sentiment classification results generated by the InSet lexicon-based approach to calculate accuracy, precision, recall, and F1-score values.while LDA topic coherence was assessed qualitatively based on the interpretability of dominant keywords within each identified topic (Nguyen et al., 2024).

3. RESULT AND DISCUSSION

3.1 Research Data

The research dataset comprises 1,001 user comments collected from a Samsung Galaxy S26 Series review video on the GadgetIn YouTube channel via web scraping using the youtube-comment-downloader Python library on March 11, 2026 (GadgetIn, 2026). The collected comments reflect a diverse range of audience responses, encompassing both positive and negative sentiments toward the reviewed device, and served as the primary data source for sentiment analysis and topic modeling in this study.

3.2 Data Preprocessing Result

Prior to analysis, the user comment data underwent a preprocessing stage to cleanse the text of irrelevant elements. The procedures carried out included case folding, cleaning, tokenization, stopword removal, and normalization (Jurafsky & Martin, 2025). This stage aimed to streamline the comment text by eliminating punctuation, special characters, and words that carry no significant analytical value. A sample of the preprocessing output, illustrating a comparison between the original comment text and the cleaned version, is presented in Table 1.

Table 1. Data Preprocessing Result

Original Review	After Preprocessing
Mantap	mantap
Inopasinya wow 💯	inovasinya wow
Monster Greenline : "yoo wassaapp!!"	monster greenline yoo wassaapp
Hati hati sama samsul	hati hati sama samsung
Percuma kalo penyakit Greenline nya masih ada	percuma kalo penyakit greenline nya masih ada

3.3 Sentiment Analysis

Following the completion of the preprocessing stage, sentiment analysis was conducted to identify prevailing opinion tendencies among users regarding the smartphone featured in the review video. Sentiment classification was performed using a lexicon-based approach leveraging the Indonesian Sentiment Lexicon (InSet) to categorize comments into positive and negative sentiment classes. The results indicate that positive sentiment constitutes the majority of audience responses, with the complete distribution of classified comments presented in Table 2.

Table 2. Sentiment Analysis Result

Sentimen	Jumlah	Persentase
Positif	665	66.4%
Negatif	336	33.6%
Total	**1001**	**100%**

3.4. Key Topics in Positive Sentiment Based on LDA

Topic modeling using the Latent Dirichlet Allocation (LDA) method applied to positively classified comments yielded three principal topics, with dominant keywords presented in Table 3.

Table 3. Main Topics in Positive Sentiment (LDA)

Topic	Dominant Keywords
Positive Topic 1	rekomendasi lebaran, beli ultra, worth it, game changer, desain terbaik,
Positive Topic 2	fitur layar, main game, mending beli, bagus ultra, update software
Positive Topic 3	privacy display, fitur privacy, display berguna, sabar nunggu, udah po

Positive Topic 1 reflects favorable evaluations of the device's quality and design, while also capturing active content requests from the audience particularly *rekomendasi lebaran* (Eid recommendation) indicating audience engagement beyond passive viewership. Expressions such as *worth it* and *game changer* further signal high perceived value toward the device. Positive Topic 2 centers on functional performance, with *mending beli* (better to buy) indicating a comparative evaluation process that reflects the alternative evaluation stage within the consumer decision-making process(Kotler & Keller, 2022). Positive Topic 3 highlights appreciation for the screen privacy feature, with *sabar nunggu* (patiently waiting) and *udah po* (already pre-ordered) suggesting that a portion of the audience had reached purchase intent prior to the device's widespread availability, implying that YouTube review content functions as a conversion driver during early product launch phases (Le et al., 2025).

Across all three positive topics, the analysis consistently reflects two dominant patterns: favorable product evaluation centered on feature innovation and design, and active audience engagement through content requests directed at the creator, collectively indicating an overall favorable reception of the Samsung Galaxy S26 Series during its initial launch phase.

From a digital business perspective, the prominence of terms such as rekomendasi lebaran, worth it, and udah po reflects the importance of micro-moments and Moment of Truth dynamics within contemporary digital marketing environments (Abbas et al., 2025). Seasonal expressions such as rekomendasi lebaran indicate that audience purchasing consideration is closely associated with culturally driven consumption periods, during which consumers actively seek trusted product recommendations through digital platforms (Alena, 2025). Simultaneously, the emergence of terms associated with pre-order intention suggests that YouTube review content may function not only as an informational medium but also as a conversion-oriented touchpoint capable of influencing consumer decision-making during the early product adoption stage. This finding reinforces the strategic role of creator-driven content in supporting digital marketing communication and seasonal campaign effectiveness within Indonesia's technology market (Ranjan & District, 2025).

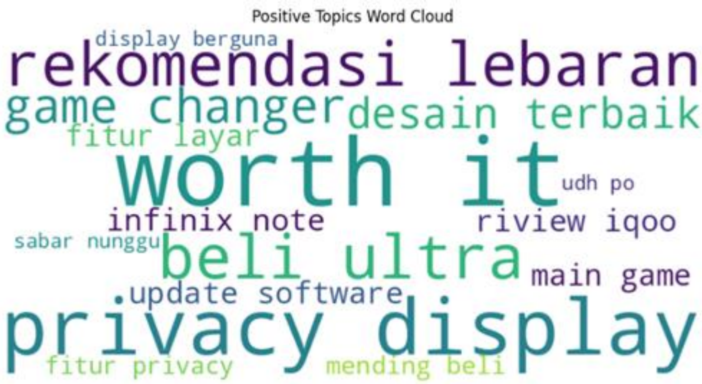

Figure 2. Word Cloud of Positive Sentiment

The word cloud in Figure 2 complements the LDA findings by illustrating overall keyword frequency. *Rekomendasi lebaran* emerges as the most visually dominant term, followed by *worth it*, *beli ultra*, and *privacy display*, indicating that creator-directed engagement and direct product appreciation constitute the two dominant patterns within positive comments. The appearance of *infinix note* and *riview iqoo* further suggests that audience interaction extended to requests for competing device reviews. While content requests are not inherently sentiment-bearing, their concentration within the positive sentiment cluster may reflect the overall favorable viewing experience that motivates audience interaction with the creator.

3.5 Key Topics in Negative Sentiment Based on LDA

In addition to positive sentiment, this study identified three principal topics within negatively classified comments, with dominant keywords presented in Table 4.

Table 4. Main Topics in Negative Sentiment (LDA)

Topic	Dominant Keywords
Negative Topic 1	setia ultra, garis hijau, sakit hati, masuk indonesia, kapok beli
Negative Topic 2	layar bergaris, ultra kotak, light saber, muncul garis, pake redmi
Negative Topic 3	green line, fitur ai, kena green, green screen, produk korea

Negative Topic 1 reflects the emotional dimension of audience dissatisfaction, where expressions such as *sakit hati* (hurt/disappointed) and *kapok beli* (reluctant to buy again) indicate a declining repurchase intention rooted in prior adverse product experiences, while *masuk indonesia* reflects apprehension toward quality consistency in the local market. Negative Topic 2 centers on the technical description of screen defects, with *light saber* used informally to describe vertical lines on the display alluding to the green line issue documented across the Samsung Galaxy product line. The appearance of *pake redmi* (using Redmi) further suggests potential brand switching among dissatisfied consumers (Shrestha, 2024). Negative Topic 3 reveals broader brand-level skepticism, with *produk korea* (Korean product) indicating that a segment of the audience associates the screen defect with Samsung's overall brand identity rather than a specific product, posing long-term reputational challenges for new product launches (Yi, 2023).

All three topics consistently converge around the screen defect issue, confirming that the green line problem constitutes the dominant concern among audiences during the initial launch period shaped more by collective memory of predecessor products than by direct experience with the S26 Series.

From the perspective of digital business and brand management, the persistence of green line discourse demonstrates how collective memory circulating within online communities may significantly affect brand equity and corporate reputation, even prior to direct product usage experience (Mustofa et al., 2024). The findings suggest that audience evaluations toward the Samsung Galaxy S26 Series were influenced not solely by current product attributes, but also by accumulated perceptions of technical issues associated with predecessor models. The appearance of comparative references such as pake redmi further indicates potential brand switching behavior among digitally connected consumers, where negative online discourse may encourage migration toward competing brands perceived as offering lower product risk (Shrestha, 2024).

In this context, management information systems and digital communication teams play a critical role in monitoring emerging social media narratives, identifying recurring consumer concerns, and implementing proactive reputation management strategies before such discourse adversely affects purchase conversion and customer trust during the product launch period (Nizma, 2025).

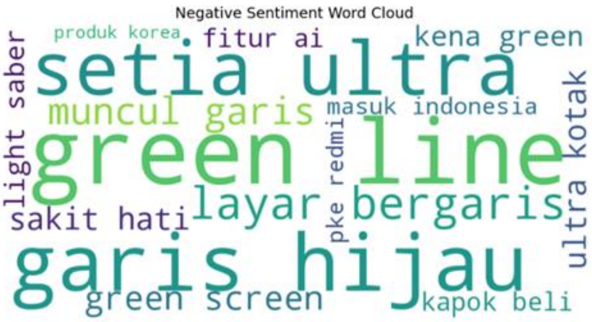

Figure 3. Word Cloud of Negative Sentiment

The word cloud in Figure 3 affirms the LDA findings, with *garis hijau*, *green line*, and *setia ultra* registering as the most dominant terms by frequency. The visual prominence of *setia ultra* within the negative cluster is particularly noteworthy, suggesting that a portion of the audience expressing concern comprises users previously familiar with the Galaxy Ultra line, whose expectations toward the new device tend to be considerably higher relative to first-time prospective buyer.

3.6 Model Evaluation

The sentiment classification results were evaluated using a confusion matrix to assess the model's performance in categorizing comments into positive and negative classes, as visualized in Figure 4.

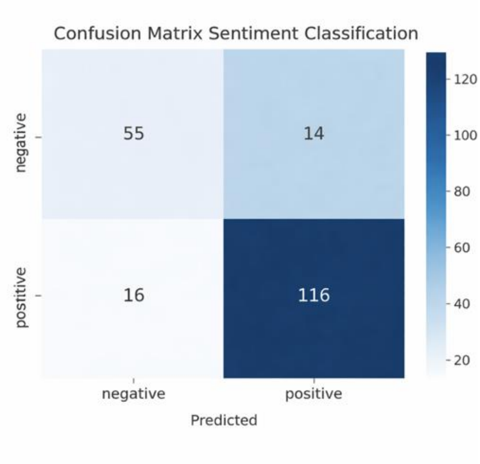

Figure 4. Confusion Matrix

Model evaluation was performed on a subset of 201 comments designated as the test set, separate from the full dataset of 1,001 comments used for sentiment classification and topic modeling. As illustrated in Figure 4 and Table 5, the model demonstrates strong performance across both sentiment classes, with an overall accuracy of 85%, indicating that the lexicon-based classification model performs reliably in capturing audience opinion tendencies toward smartphone review content.

Table 5. Sentiment Classification Evaluation Metrics

Class	Precision	Recall	F1-Score	Support
Negative	0.77	0.80	0.78	69
Positive	0.89	0.88	0.89	132
Accuracy			0.85	201
Macro Average	0.83	0.84	0.83	201
Weighted Average	0.85	0.85	0.85	201

3.7 Discussion and Implication

The findings indicate that the majority of audience comments on the Samsung Galaxy S26 Series review video reflect positive sentiment, suggesting that smartphone review content on YouTube tends to foster favorable perceptions among viewers. While no prior study has specifically examined the same research object, the findings are consistent with research employing comparable approaches in the context of other product reviews on YouTube, which broadly report a dominance of positive sentiment within high-engagement review content (Toussaint et al., 2022). This affirms that YouTube has evolved into an influential electronic word-of-mouth space that shapes consumer perceptions of technology products (Liu & Jayawardhena, 2024).

Topics emerging within positive comments predominantly relate to feature innovation, device design, and favorable product evaluations, while also reflecting active audience engagement through content requests directed at the creator. This pattern suggests that audiences not only evaluate products on technical and aesthetic grounds, but also interact with review content as a participatory medium, a behavioral pattern indicative of high audience investment in the creator's content (Tarnovskaya et al., 2025).

Negative sentiment comments, by contrast, are predominantly centered on concerns surrounding the green line issue a notable finding given that the device had only recently launched and the majority of the audience had yet to accumulate direct usage experience. This indicates that the negative perceptions formed were more strongly shaped by collective memory of product quality issues from previous series than by actual experience with the Samsung Galaxy S26 Series. This finding highlights how consumer evaluations of newly launched products may be influenced not only by current product information but also by accumulated perceptions of previous product generations, reinforcing the role of brand reputation in shaping early-stage consumer judgment (Yi, 2023).

From a digital business perspective, the findings also demonstrate the importance of Moment of Truth dynamics within technology product marketing. Positive audience responses associated with terms such as worth it, rekomendasi lebaran, and pre-order expressions indicate that YouTube review content functions not merely as an information source, but also as a strategic touchpoint influencing consumer purchase consideration during critical decision-making moments (Lo et al., 2026). Simultaneously, the persistence of green line discourse highlights how collective memory preserved within digital communities may negatively affect brand equity and corporate reputation across subsequent product generations (Prasetio & Azmi, 2024). The emergence of references to competing brands such as Redmi and Infinix further suggests potential brand switching behavior among digitally connected consumers, emphasizing the necessity for technology vendors to integrate social media monitoring and sentiment analytics into management information systems to proactively mitigate reputational risks during product launch periods (Keller, 2020).

In terms of practical implications, the findings offer several pertinent insights for digital marketing strategy. First, the dominance of positive sentiment during the initial launch phase suggests that YouTube review content plays a significant role in establishing favorable early consumer perceptions of new products, positioning the platform as a relevant channel within digital marketing communication strategies during the product introduction phase (Le et al., 2025). Second, the pronounced presence of green line concerns within negative comments despite the product not yet being widely used indicates that reputation management addressing historically rooted issues warrants integration into Samsung's communication strategy, particularly through proactive engagement with consumer apprehensions in digital spaces (Ratnayaka et al., 2024). Third, YouTube comment analysis demonstrates its value as a source of consumer intelligence, enabling marketers to gain insight into audience perceptions, concerns, and deliberation patterns during the critical period surrounding a product launch (Ju & others, 2024).

4. CONCLUSION AND RECOMMENDATIONS

4.1. Conclusion

This study aimed to analyze sentiment and identify dominant discussion topics within user comments on a Samsung Galaxy S26 Series smartphone review video on YouTube. Analysis of 1,001 user comments revealed that 665 comments (66.4%) were classified as positive sentiment and 336 comments (33.6%) as negative sentiment. Topic modeling results using the Latent Dirichlet Allocation (LDA) method indicate that positive comments predominantly revolve around device features, smartphone design, and favorable product evaluations, while also reflecting active audience engagement through content requests directed at the creator. Negative comments, by contrast, are largely dominated by concerns over screen reliability issues, particularly the green line problem historically associated with Samsung Galaxy devices. Notably, the prominence of these concerns prior to any direct usage experience suggests that consumer perception during a product's initial launch phase is substantially shaped by collective memory of predecessor products rather than firsthand experience. These findings affirm the value of YouTube comment analysis as a source of consumer intelligence for digital marketing practitioners, particularly in monitoring brand perception and anticipating reputational challenges during new product launch phases.

4.2. Recommendations

Future research is encouraged to utilize larger datasets drawn from multiple social media platforms to yield a more comprehensive representation of consumer perception. The application of machine learning or deep learning-based sentiment analysis methods is also recommended to provide a methodological comparison and further explore the potential performance gains relative to the lexicon-based approach adopted in this study. Practically, smartphone manufacturers and technology content creators may leverage YouTube comment analysis as a valuable source of consumer intelligence in informing product communication strategies.

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