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Analyzing Consumer Purchase Decisions Toward Eyeshadow Products Through Sentiment Analysis and Social Network Analysis on X (Twitter)

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Abstract. This study examined the consumers' decisions on how to purchase eyeshadow products from Twitter/X conversations using Sentiment Analysis and Social Network Analysis (SNA). The research aimed to investigate the sentiment of consumers, interaction, influence of influential people, and communication structures of eyeshadow products in the social media marketing and the social media communication. We employed data collected from Twitter/X through SocialX as a quantitative computational social science approach to the research. The dataset comprised 218 records between January 1, 2026, and April 30, 2026, with eyeshadow, e.g., eye-shadow, eye-shadow review, eye-shadow recommendation, and eye-shadow discussion. We combined sentiment analysis, emotion analysis, text network analysis, trend analysis, and social network analysis to investigate consumers' interactions and information sharing. We find that Twitter/X discussions regarding eyeshadow products are dominated by suggestions, product reviews, and information sharing. As a result, the sentiment analysis showed that neutral and positive sentiment dominated the discussion and the emotional representation was the most dominant emotion. The Social Network Analysis identified several key actors who are in the network and were involved in connecting discussion clusters and communicating cosmetic information. The findings show that the social media interactions were a major factor in the understanding of consumers' decision to purchase eyeshadow products. The recommendations, positive perception of the product, and the well-connected digital communication structures of Twitter/X have shown that Twitter/X is a very effective source to exchange product information and to shape cosmetic purchasing in beauty online communities.

Keywords: Sentiment Analysis, Social Network Analysis, Consumer Purchase Decision, Eyeshadow, Twitter/X

1 Introduction

The digital beauty industry has revolutionized the way cosmetics are sold, even eyeshadow products [1]. With regard to information sharing, consumers' use of social

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media is no longer simply a medium of conversation but also one of the largest and most used sites for them to access brands' information, make competitive comparisons and write reviews about them [2]. This is why Instagram has become one of the most popular platforms for cosmetic brands, thanks to the images, vids, reels and influencer marketing. Twitter/X also provides a forum for consumers to express their thoughts, feelings and opinions in an open and transparent way [3]. As the beauty content creators and brand collabs have become a common occurrence on Instagram, the competition between cosmetics brands to attract their audience's attention and patronize loyalty continues to reach a whole new level [4].

Digital marketing strategies in Instagram should boost the consumers' buying decisions by providing attractive, credible and interactive product information [5]. But much of the promotion activity in Instagram does not necessarily result in purchases, as it is known [6]. However, many customers are unsure about eye-shadow products owing to the fact that the colour consistency, pigment stability, product du-rability and marketing visuals or product outcomes are not the same [7]. And this difference is also clear in user conversations on Twitter/X, as the product customers openly express their disappointment or satisfaction after purchasing eye-shadow products they found on Instagram promotions [8]. This disconnect, both in digital marketing, for which they can promote purchase decisions and in social media for people who are still uncertain, critical and have different opinions about eyeshadow products [9]. Honestly, no one knows what to think about these cosmetics yet, and they have to fight over them while they're not sure if they're the same or different. In order to gain insights into how digital marketing strategies impact consumer buying decisions in the broader context, it is crucial to research consumer attitudes and interactions on social media platforms [10].

The correlation of social media and consumer buying behaviour is extensively researched in the beauty industry in recent years [11]. It has been confirmed that visual marketing, e-WOM and Instagram user-generated content have a strong impact on the consumers' purchasing interest and purchase decision for cosmetic products [10]. Customers are more likely to rely on what other customers have said about a product than what the companies say in their formal advertising copy [12]. Twitter/X is becoming increasingly vital to understand consumer perceptions that are not influenced by brands, as a key site for peer recommendations in digital communities [13]. Recently, several studies have also been conducted to identify the perceptions of the consumers about cosmetic products using sentiment analysis techniques from social media [14]. This method is adopted to quantify positive, negative and neutral sentiments from digital conversations about beauty products [15]. Social Network Analysis (SNA), communication network structures, information dissemination patterns, and dominant actors that shape public opinion formation in social media environments have been investigated [16]. These technological advancements have enabled researchers to have more ad-vanced tools and data to gain a deeper understanding of digital consumer behavior with a different emphasis than the general survey-based approach [17].

Most previous research studies, however, have been limited to studying the direct relationship between Instagram and purchase intention or brand engagement. Howev-

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er, there is limited research that has been conducted to assess the purchase decision of eye shadow products using sentiment analysis and Social Network Analysis using Twitter/X data. In addition, previous research has largely concentrated on visual marketing and engagement, with overlooking the role of customer feelings on digital interaction networks and the cumulative effect of these feelings on customer purchasing decisions [18].

There are a few gaps in knowledge that have not been tackled in the literature. The first is that most of the previous researches have studied only the direct connection between Instagram marketing and purchase intention, and consumer feelings are conveyed via social media platforms to make purchase decisions based on eyeshadow product sales [10]. Previous research has used traditional quantitative methods (surveys and regression analysis) that do not consider the dynamic nature of real-time digital interactions in social media platforms, including the conversation of the Twitter/X platform, and can capture more detailed information on how users feel about the experience, satisfaction with cosmetic products and customer dissatisfaction [14]. Negative or positive messages have not yet been analysed at the network level in order to gain a deeper understanding of how they are embedded in user communities [19]. Third, sentiment analysis and social network analysis to evaluate Instagram marketing to customers' purchase decisions for eyeshadow prod-ucts is still being explored in this field [20].

The previous studies have taken apart the fields of sentiment analysis and social network analysis, resulting in a very poor understanding of the correlation between consumer perception and the structure of digital interactions [21]. This study has novelty in the use of Sentiment analysis and Social Network Analysis to analyses the decision-making process of eye-shadow purchases from the conversations of the consumer on Twitter/X with the Insta-gram marketing activities. By combining the methodological perspectives, this research provides a more comprehensive view of the formation of a digital opinion ecosystem and how it finally affects consumers' purchasing and non-purchasing choices of eye shadow products [22].

To sharpen this contribution, it is useful to clarify what specifically distinguishes this study from prior sentiment-analysis and Social Network Analysis research on cosmetic and beauty products. Whereas earlier studies have typically applied either sentiment analysis or network analysis in isolation to a single cosmetic category, and have rarely linked social media discourse back to a specific upstream marketing channel, this study integrates five complementary analytical layers (sentiment, emotion, text-network, trend, and social-network analysis) within a single dataset and explicitly relates Twitter/X discourse to Intagram-driven eyeshadow marketing. The theoretical contribution therefore lies not in the individual techniques, which are indeed well established, but in demonstrating how a multi-method, cross-platform lens can trace the diffusion of digital opinion from a visually driven marketing platform into a text-based peer-discussion platform. This extends Consumer Decision- Marketing Theory by showing that its e-WOM and social-influence components are not confined to a single platform but travel across platforms, and that the intensity and structure of this cross-platform diffusion can be measured through network centrality and sentiment distribution rather than inferred survey self-reports alone.

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This method is not just used to determine the trend of consumer sentiment for eye shadow products, but also opinion dissemination and dominant actors in digital social networks [23]. Moreover, this research involves real user interactions on social media that are subsequently extracted, analyzed, and translated into social media marketing data, which allows for more empirical and dynamic understanding of the relationship between Instagram marketing strategies and consumer perceptions and purchases [5]. This study is grounded in the Consumer Decision-Making Theory, which argues that the purchasing decision is affected by the information evaluation process, social perception, consumer experiences, and factors in the digital environment. There are two components to examine the impact of digital opinions on consumers' buying decisions: social media e-WOM and social influence. In the context of social media, these two factors provide explanations for the impact of digital opinions on consumers' buying decisions: social media e-WOM and social influence. [24].

This study aims to analyze consumer sentiments toward eyeshadow products marketed on Instagram based on Twitter/X conversations and identify key actors in digital social networks and how sentiment patterns and social networks affect consumers' decision making towards eyeshadow products. Therefore, this study addresses the following research questions: (1) How are consumer sentiments toward eyeshadow products promoted through Instagram expressed and distributed within Twitter/X interaction networks? (2) Who are the key actors in the Twitter/X social network, and how do they influence sentiment dissemination related to Instagram-based eyeshadow marketing activities? (3) To what extent can Twitter/X-based sentiment patterns and network structures complement the evaluation of Instagram marketing effectiveness in influencing consumers' purchase decisions toward eyeshadow products?

It is also important to clarify how "purchase decision" is operationalized in this study. The Twitter/X dataset does not contain direct transaction records; rather, it captures discussions, product reviews, recommendations, and opinions that consumers share before, during, and after forming a purchase judgment. Consistent with Consumer Decision-Making Theory and the electronic word-of-mouth (e-WOM) literature, this study treats these discursive indicators, such as recommendation-seeking, product evaluation, and expressed satisfaction or dissatisfaction, as proxies for the information-evaluation and social-influence stages that preced an actual purchase, rather than as evidence of completed transactions. Accordingly, the term "purchase decision" in this study refers to decision-relevant discourse and purchase related attitudes expressed by consumers, and conclusions about actual buying behavior should be interpreted as inferential rather than directly observed.

Regarding the relationship between Instagram and Twitter/X in this study, Intagram is treated as primary marketing and visual-contect channel through which eyeshadow products are promoted, while Twitter/X is treated as the observation window through which the resulting consumer reactions, whether originating from instgram promotions or from independent produt experiences, are expressed and discussed. Because the dataset was collected from Twitter/X rather than Instagram, the findings speak most directly to how consumers talk about eyeshadow product on Twitter/X, and Instagram's role is inferred from users' own references to promotions,influencers, and visual contect rather than measured directly from Instagram

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data. This distinctions is treated as a limitation of the current design, and conclusions regarding Intagram's marketing effectiveness are presented as complementary evidence rather than a direct evaluation of Instagram-based campaigns.

2 Methods

This study used quantitative research method and a computational social science approach to study consumer purchase decisions about eyeshadow products via Twitter/X social media interactions [25]. Social Network Analysis (SNA) was used to examine the interaction patterns, communication structure and information dissemination on eyeshadow products discussed in social media interactions. The method was designed to analyze consumer information, network structure and influential users in Instagram cosmetics marketing activities [26]. This computational method since it can be used in a more efficient way to analyze digital interactions that are natural and more authentic than survey-based ones [27].

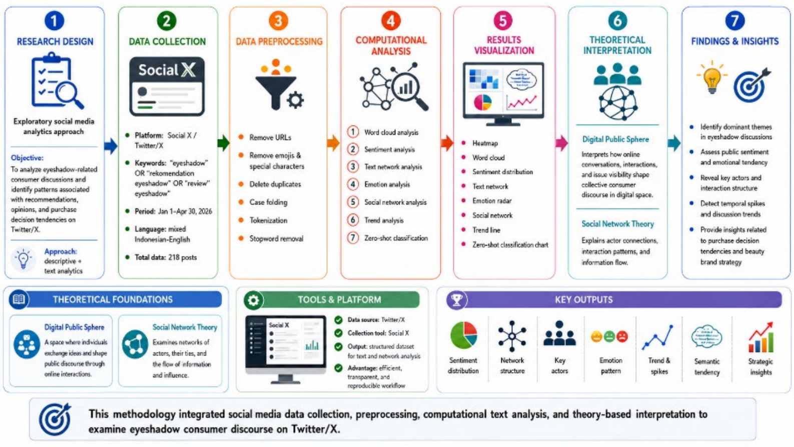

Fig. 1. Research Methodology Framework

The research data was collected from Twitter/X in SocialX as the primary social media crawling and analysis tool. The data were collected using keywords related to eyeshadow product discussions such as "eyeshadow," "eyeshadow review," "rekomendasi eyeshadow," and "favorite eyeshadow," and so on. Indonesian-language discussions were targeted in this dataset for the context of local consumer behavior, communication, and digital interaction. The keywords were selected early from trending beauty discussions on Twitter/X so that the data is full of consumer discussion around eyeshadow products [28].

Because the keyword strategy relied on explicitly review and recommendation oriented terms such as "eyeshadow review," "rekomendasi eyeshadow", and "favorite eyeshadow", the resulting dataset is likely to over-represent users who were already engaged with, or favorably disposed toward, eyeshadow products, while underrepre-

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senting silent dissatisfied customers and casual mentions phrased with brand names, slang, or indirect references that do not contain these keywords. This keyword-driven sampling approach is therefore a potential source of selection bias, and the neutral-to-positive sentiment distribution reported in this study should be interpreted in light of bias rather than as a fully representative picture of all eyeshadow-related opinion on Twiiter/X.

The data collection period started from 1 January 2026 to 30 April 2026 with a maximum crawling limit of 250 posts. The total number of valid Twitter/X records was 218 and we used it as the main data set for analysis. The data included tweets, replies, mentions, hashtags and interaction between users who discussed eyeshadow products and related cosmetic experiences. We chose the 4-month collection period for this study so as to capture the seasonal behavior of consumer purchasing behavior, especially around the major promotional events in the Indonesian cosmetic market [29].

With respect to the adequacy of the sample, the 218 record analyzed here are not intended to represent the full volume of beauty-related discussion on social media, but rather to provide an in-depth, closely examined case within a bounded keyword scope and time window, consistent with the exploratory, computational social-science approach adopted in this study. The four-month window, consistent with the exploratory, computational social-science approach adopted in this wtudy. The four-month window and the maximum crawling limit of 250 posts were chosen to balance data richness against the practical constraints of manual data cleaning and validation; a larger, multi-platform, and longer-term sample would be needed before the sentiment and network patterns identified here could be generalized to the broader population of Indonesian eyeshadow consumers, and this constraint is discussed further in the Limitations section.

The research process was organized chronologically from the beginning of research goals and keyword formulation, and social media data crawled through SocialX. Data cleaning and filtering was done after data collection to remove duplicative, irrelevant, and incomplete data. During this process, spam messages, bot-generated messages, and posts unrelated to cosmetic product discussions were excluded to ensure quality and relevance of the data [30]. The cleaned data was then analyzed using Social Network Analysis software in the SocialX platform.

The Social Network Analysis process was conducted to identify network structure, interactions, communication clusters and influential parties in the Twitter/X conversation network [31]. The network was analyzed based on degree centrality, betweenness centrality, closeness centrality and network density to identify the top users and information dissemination patterns in the digital network. Users' interactions also influenced consumer perception and purchasing decision for eye-shadow products [25]. Degree centrality was highlighted in the analysis as it is the most important indicator of how much user engagement is present and how many accounts were information hubs in the network [32].

Among the network metrics available in SocialX, degree, betweenness, and closeness centrality, together with overall network density, were selected because they directly correspond to the research questions concerning who the key actors are and

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how they connect discussion clusters. Degree centrality identifies accounts with the highest direct engagement (mentions and replies), betweenness centrality identifies accounts that act as bridges between otherwise separate discussion clusters, and closeness centrality identifies accounts positioned to reach the wider network quickly, while network density describes how tightly the overall conversation is interconnected. Eigenvector centrality and PageRank, which weight a node's influence by the influence of its neighbors, were not computed in this study because the SocialX platform's default network module does not output these measures for the dataset size analyzed here; this is noted as a methodological constraint, and future studies with access to raw network edge lists are encouraged to apply eigenvector-based measures for a more complete picture of influence propagation.

The methodology was organized in a systematic manner to ensure that all the analysis steps were in accordance with the goals of the research [33]. Social Network Analysis provided a feasible framework for understanding consumer engagement and digital communication and how this information can be used to influence opinions and purchase decisions in social media and how it is connected to data [34]. The sequential and linked nature of each step of the analysis made it possible to see network analysis data in terms of consumer sentiment patterns on the dataset [35].

This study was based on real-time social media data from Twitter/X conversations and scientific computations [36]. The use of SocialX as an analytical tool helped to ensure that network mapping and interaction visualization was reliable and with the use of existing Social Network Analysis indicators it was scientifically valid and the analysis methods were valid [37].

The sentiment and emotion classification in this study were generated through the built-in natural-language-processing models provided by the SocialX platform, which apply lexicon- and machine-learning-based classification to Indonesian- and English-language social media text and assign each record to a discrete sentiment or emotion category. Because these models were not independently retrained or fine-tuned for the eyeshadow-discussion domain in this study, no separate accuracy or F1-score validation against a manually labeled subsample was performed, nor were the emotion categories manually verified or benchmarked against human annotators; this represents a methodological limitation. Automated sentiment and emotion classifiers of this kind are known to have reduced accuracy when processing informal language, code-mixed Indonesian-English expressions, sarcasm, and mixed or ambiguous sentiment, all of which are common in beauty-related social media conversations [21]. Readers should therefore interpret the sentiment and emotion distributions reported in this study as indicative patterns generated by an automated classifier rather than as human-validated ground truth; this limitation is revisited in the Limitations and Recommendations section.

This study was also done to be reproducible through a clear description of data collection period, keywords, dataset size, analytical platform and network analysis procedure [38]. Future researchers may be able to replicate the study using the same keywords, time periods and analysis tool to compare findings in cosmetic product categories or social media channels [25].

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3 Result and Discussion

This section presented the results of the analysis of the Twitter/X data collected using the Social X application. The dataset consisted of 218 posts collected from January to April 2026 with keywords for eyeshadow, recommendation and review. The results were organized according to the analytical steps as follows: data overview, word cloud analysis, sentiment analysis, text network analysis, emotion analysis, social network analysis, trend analysis and zero-shot classification. All the analyses were systematically presented to clarify the main patterns of the data and to help understand the conversations of the users about eye-shadow products. Overall, research showed that the Twitter/X users were more interested in recommendations, reviews, product quality, shade, pigmentation, price and palette preferences. The visual analysis shows that the conversation was not evenly distributed during the observation period, with several increases in post frequency occurring toward the end of April. In addition, the sentiment and classification results showed that consumer discussions were dominated by neutral and positive expressions, although some negative opinions were also identified. These results provide a snapshot of the consumers' opinions, preferences, and purchase-related attitude towards eyeshadow products (from Twitter/X) by using data collected from the Social X application.

3.1 Data Overview

Based on the data collected from Twitter/X via SocialX, 218 conversation records on eyeshadow products were successfully collected during the observation period from January 1, 2026, to April 30, 2026. The data were collected with keywords "eyeshadow," "eyeshadow review," "rekomendasi eyeshadow," and "favorite eyeshadow," with Indonesian-language filtering. We plotted the data on a heatmap to show the different levels of tweet activity based on the date and hour of interaction. The heatmap showed that the conversation on eyeshadow products was intermittent during January and February 2026, indicating that discussions on eyeshadow products were very low and scarce during the beginning of the year. However, the interaction activity gradually increased in March and reached the highest intensity at the end of April 2026.

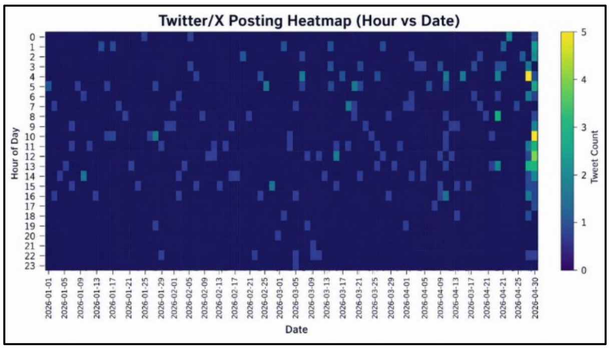

Fig. 2. Data Overview . Source: X/Twitter data processed via Social X (2026).

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The visualization also indicated that the most active periods of Twitter/X discussions were during the day and evening (10:00-16:00) as some dates had higher Twitter activity than the other time periods. Moreover, the highest activity peaks were near the end of April 2026, suggesting that more people were paying attention to eyeshadow questions on Twitter/X during this time period.

The peak in the activity of tweets at the end of the observation period indicated the dynamic nature of discussions on cosmetic issues on social media. The increase of the conversation intensity could reflect the influence of the promotional campaigns, product recommendations, beauty trends, influencer discussions, or viral cosmetic content on social media sites.

Overall, the data summary showed that Twitter/X discussions about eyeshadow products were actively happening on different dates and time periods and that this is a dynamic interaction pattern that can be further studied on social networks. The results also confirmed that social media platforms provided valuable real-time consumer interaction data that could help with the evaluation of purchase decision behavior toward cosmetic products.

3.2 Wordcloud Analysis

The word cloud analysis revealed the most common terms in Twitter/X conversations related to eyeshadow products during the observation period. The visualization was generated from 218 Twitter/X records and showed the intensity and frequency of words used by users when discussing eyeshadow products, recommendations, product quality, and cosmetic preferences.

Fig. 3. Word Cloud Analysis. Source: X/Twitter data processed via Social X (2026)

Based on the visualization, we observed that the keyword 'eyeshadow' was the most popular in the conversation network, meaning that the data collected was very relevant to the research topic. The second most popular term was 'rek-omendasi', which indicates that most Twitter/X users actively looked for and shared product recommendations related to eyeshadow products. This indicates that discussions about recommendations made a huge impact on consumer purchase considerations in the digital cosmetic community.

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Other common words that appeared frequently included “review,” “palette,” “pigmented,” “warna,” “make up,” “bagus,” “murah” and “shade.” These words indicate that users frequently mentioned quality of products such as pigmentation, color, product affordability and palette preferences. Words like “pemula,” “make,” “pakai,” “cocok,” “saran” indicated that many users were also looking for practical guidance and recommendations in terms of product quality and regarding for beginners what is a good eyeshadow to buy or use.

And, there were also cosmetic-related terms outside the core keyword context, like “blush,” “lip,” “eyeliner,” “contour,” “parfum,” etc., which means that conversations about eyeshadow products were often part of the makeup and beauty product conversation. The word cloud analysis also revealed emotions-laden words like “suka”, “cantik,” “aman” and “jujur”, which indicates that consumers frequently express their own opinions and subjective feelings about cosmetic products.

3.3 Sentiment Analysis

The sentiment analysis results showed the public opinion of eyeshadow products on Twitter/X during the observation period. We analyzed 218 conversations and the sentiment classification categorized them into 3 categories: positive, neutral and negative. Based on the analysis results, neutral sentiment was the most common sentiment in the discussions, 204 records or 93.58% of the total data. Most of the people discussed eyeshadow products on Twitter/X in a non-emotional way, rather in a kind of description or recommendation. In total, positive sentiment was 8 records or 3.67% of the conversations and was generally in agreement with the product quality, pigmentation, color, price and suitability for makeup application.

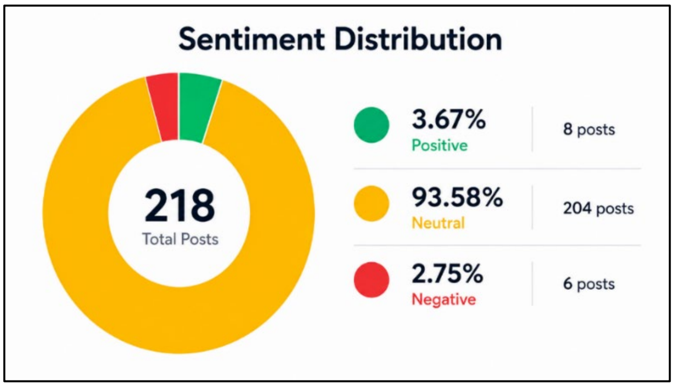

Fig. 4. Sentiment Distrubtion of Eyeshadow.
Source: X/Twitter data processed via Social X (2026)

Negative sentiment represented 6 records, or 2.75% of the data set. Most negative conversations involved customer complaints about product performance, color mismatch, durability issues, or personal disappointment after using the product. The proportion of negative sentiments was relatively small, but it shows that there are still

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some consumers that have negative opinions and experiences in Twitter/X about eyeshadow products. Overall, sentiment analysis results showed that consumer feedback towards eyeshadow products on Twitter/X was largely based on information exchange, recommendation activities, and product evaluation discussions. These findings supported the relevance of social media sentiment analysis in understanding consumer behavior in digital media and how online conversations impact the decision-making process of users in the beauty industry.

3.4 Text Network Analysis

The text network analysis illustrated the relationship patterns among dominant keywords that appeared in Twitter/X conversations regarding eyeshadow products. The visualization mapped how words were interconnected within user discussions, allowing the identification of central topics, frequently associated terms, and covesation clusters related to eyeshadow purchase considerations

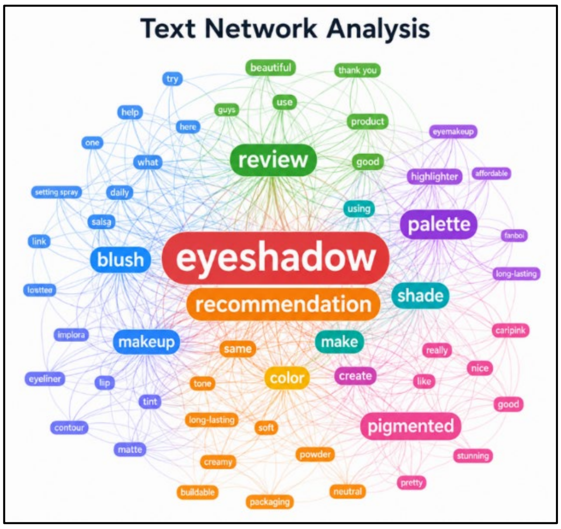

Fig. 5. Text Network Analysis. Source: X/Twitter data processed via Social X (2026)

Based on the network visualization, the keyword eyeshadow was one of the most discussed and well-connected nodes in the interaction network. The keyword was also associated with other important terms like “rekomendasi,” “review,” “palette,” “pigmented,” “warna,” “make up” and “produk” and also strongly connected with many nodes in the network. This means that recommendation-seeking and recommendation-sharing activities are very active in the Twitter/X beauty community. The text network analysis also showed that recommendation-based discussions and product review activities are on the top of the digital communication structure. Many product evaluation terms like “pigmented,” “warna,” “palette,” “shade,” “bagus” and “murah” were interrelated between the central nodes.

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3.5 Emotion Analysis

The emotion analysis results illustrated the emotional distribution expressed within Twitter/X conversations related to eyeshadow products. The emotional classification categorized user expressions into five emotional dimensions: happy, fear, sadness, anger, and love.

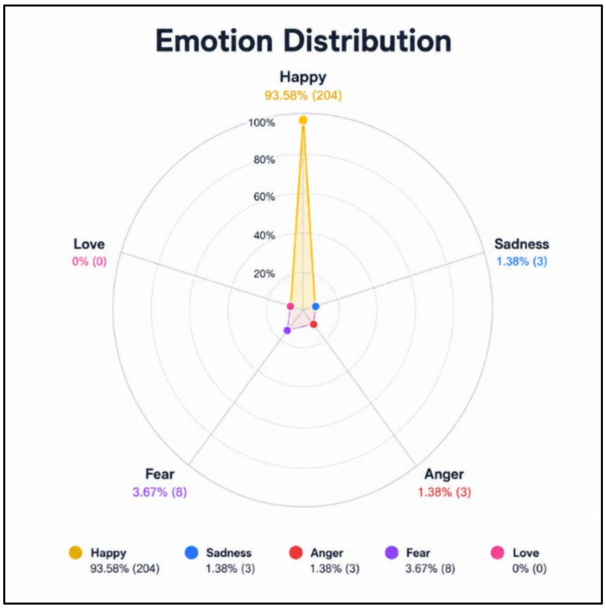

Fig. 6. Emotional Distribution. Source: X/Twitter data processed via Social X (2026)

From the visualization results, the happy emotion dominated the overall conversation network by 204 records or 93.58% of the total conversation network. The fear emotion was 8 records or 3.67%, meaning the consumer had some problems with product suitability, quality, or buying decisions as well. Sadness and anger were 3 records each or 1.38% of those with no data from it, and love was just 0% of the total. Overall, the emotion analysis showed that the Twitter/X discussions regarding eyeshadow products were dominated by positive feelings. Happy emotions were most prevalent and showed that the digital beauty community users were more likely to engage in positive communication behavior, recommend, and have high-quality product discussions.

3.6 Social Network Analysis

The social network analysis illustrated the interaction structure among Twitter/X users discussing eyeshadow products during the observation period. The network visualization mapped the relationships among user accounts based on mentions, replies, and interaction activities collected through the SocialX platform.

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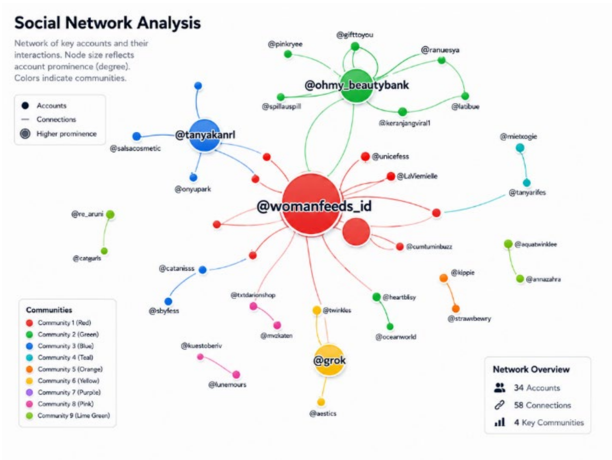

Fig. 7. Social Network Analysis. Source: X/Twitter data processed via Social X (2026)

Based on the visualization results, some accounts were found to be the central nodes of the network with larger sizes and higher connectivity. The account @womanfeeds_id appeared to be the most influential one in the interaction network. The accounts @ohmy_beautybank, @tanyakanrl, and @grok also became influential nodes in the network. They formed the main interaction clusters connected to many smaller accounts. It is clear that these accounts acted as communication hubs in the beauty-related discussion space. The network structure also showed the existence of multiple smaller clusters connected through central actors. The visualization further showed that the network density was fairly concentrated around recommendation and review-oriented discussions. From the interaction perspective, the social network analysis showed that the communication in the eyeshadow discussion network was dominated by a few very connected accounts.

It should also be noted that this analysis was conducted at the product-category level rather than the brand level; that is, all eyeshadow-related conversations were pooled together regardless of the specific brand being discussed. Because different eyeshadow brands vary in price, quality positioning, and target audience, sentiment and network structures may differ substantially from one brand to another, and the influential accounts identified here may play different roles depending on which brand or product line is being discussed. A brand-level or product-level breakdown was beyond the scope of the present study and is recommended as a direction for future research.

3.7 Trend Analysis

The trend analysis illustrated the fluctuation of Twitter/X conversation activity related to eyeshadow products during the observation period. The visualization presented daily conversation frequency, a 7-day moving average, and spike events that reflected significant increases in discussion intensity.

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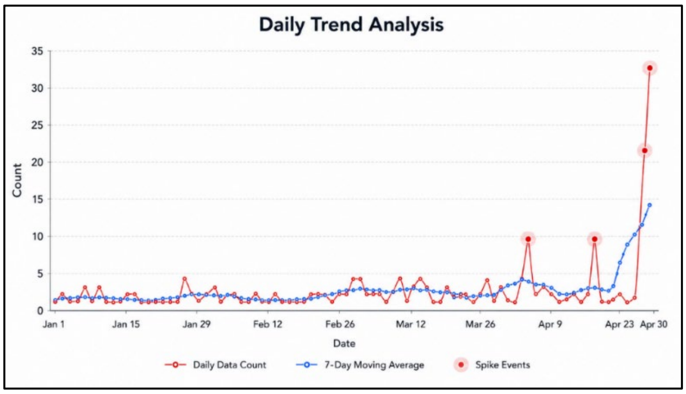

Fig. 8. Trend Analysis. Source: X/Twitter data processed via Social X (2026)

Based on the visualization results, conversation activity remained relatively low in January and February 2026, with a conversation volume between 1 and 4 conversations per day. The 7-day moving average line shows a gradual upward trend starting in early March 2026. Several spike events were identified throughout the observation period, particularly at the end of March and during April 2026. The most significant spike occurred on April 30, 2026, where conversation volume sharply increased to the highest level observed in the dataset. In general, the trend analysis showed that the Twitter/X conversations about eyeshadow products were mostly fluctuating but gradually increasing in action during the period of observation. This suggests that social media platforms were instrumental in ongoing consumer interactions, recommendation sharing, and product-related discussions.

3.8 Zero-Shot Classification

The Zero-Shot Classification analysis illustrated the distribution of semantic sentiment categories identified from Twitter/X conversations. The classification process categorized the conversations into three primary semantic labels: positive, negative, and neutral.

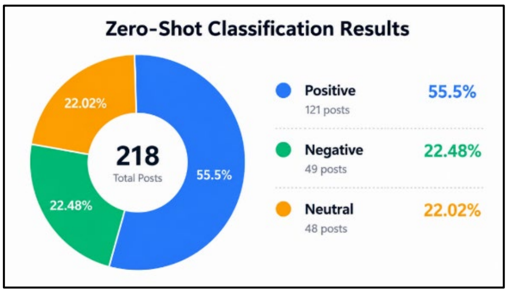

Fig. 9. Zero-Short Sentiment Classification.
Source: X/Twitter data processed via Social X (2026)

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Based on the visualization results, the positive category occupied 121 records or 55.5 percent of the total conversation data. The negative category accounted for 49 records or 22.48 percent of the data, meaning that a large number of users criticised or disagreed with eyeshadow products. The neutral category occupied 48 records or 22.02 percent of the data. The classification distribution showed positive semantic interpretations and negative semantic interpretations were more prevalent among the two categories in the observed discussion network. The relatively balanced distribution of negative and neutral categories showed that consumers were not only more likely to say positive things but they were also likely to experience good things about the products and be critical about the products.

4 Conclusion

This study concluded that Twitter/X conversations about eyeshadow products are dominated by recommendation sharing activities, product reviews and discussions about the beauty industry in digital beauty communities. As mentioned earlier, sentiment analysis, emotion analysis, text network analysis, trend analysis and Social Network Analysis showed that in general people on social media are positive and neutral about eyeshadow products. Recommendation-based discussions, product reviews and makeup experiences are the topics that users discussed a lot in the Twitter/X social network. Moreover, the findings showed that Twitter/X sentiment patterns and networks that were established to influence Instagram marketing to the consumers in eyeshadow products. The research study, on the whole, contributed to the understanding of digital consumer behavior in the beauty industry by combining sentiment analysis and Social Network Analysis. The results indicate that social media platforms were not only communication channels but also collaborative digital environments that facilitated information sharing as well as information exchange, consumer interaction and product evaluation in cosmetic purchasing behavior.

From a managerial perspective, these findings offer several practical implications for cosmetic brands and marketers. First, because a small number of highly connected accounts, such as the beauty-community and recommendation accounts identified in the network analysis, act as communication hubs, brands should prioritize identifying and collaborating with these naturally emergent opinion leaders, rather than relying solely on follower count, when selecting influencers for eyeshadow campaigns. Second, since recommendation-seeking and product-review language dominate the discussion, brands should actively monitor and respond to electronic word-of-mouth (e-WOM) on Twitter/X, using timely responses to negative or uncertain comments to manage product reputation before dissatisfaction spreads through well-connected clusters. Third, the concentration of conversation around recommendation and review topics suggests that community-engagement strategies, such as hosting question-and-answer threads, shade-matching guides, or user-generated review campaigns, are likely to resonate more strongly than purely promotional content. Finally, brands designing digital campaigns should coordinate messaging across Instagram and Twitter/X, since consumer discourse observed on Twitter/X often references Instagram-

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based promotions, and inconsistent messaging across platforms may contribute to the mixed sentiment and uncertainty documented in this study.

5 Limitations and Recommendations for Further Research

This study had several limitations. First, the data was just Twitter/X and may not represent the overall behaviour and opinions of cosmetic consumers across different social media platforms. Second, 218 records were collected within a short time period which might not capture more in-depth conversations and seasonal changes in the beauty industry. Third, the study only focused on keyword-based conversations and may have excluded discussions using other terminology and indirect references to cosmetic products. In addition, the sentiment and emotion classification was done with automated analysis where sarcasm, context-based meaning and mixed emotional expressions may have been considered. We urge future research to increase the scope of the analysis by working on multiple social media sites such as Instagram, TikTok, and YouTube. Further studies might also require more information and longer observation time. We would like future researchers to combine Social Network Analysis with advanced machine learning or deep learning to improve classification accuracy.

Beyond the limitations noted above, several additional constraints should be acknowledged. This study treated eyeshadow products as a single undifferentiated category and did not conduct brand-level or product-level analysis; because different eyeshadow brands vary in price, quality positioning, and target audience, sentiment and network patterns may differ substantially across brands, and future research should disaggregate the dataset by brand to test this possibility. In addition, because the dataset reflects online discourse, such as reviews, recommendations, and opinions, rather than verified purchase records, the conclusions regarding “purchase decisions” should be understood as inferences about purchase-related attitudes and discourse rather than direct measurements of completed transactions. The keyword-based sampling strategy may also have introduced selection bias toward consumers who were already engaged with or favorably disposed toward eyeshadow products, and the automated sentiment and emotion classifiers used in this study were not independently validated against human-annotated data, which may affect the accuracy of the reported sentiment and emotion distributions, particularly for sarcastic, mixed, or context-dependent expressions.

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