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Mapping Consumer Sentiment and Network Dynamics of Perfume Co-Branding Discourse on X/Twitter: A Computational Social Network Analysis Approach

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Abstract. The rapid growth of the global fragrance industry has driven brands to adopt co-branding strategies to strengthen brand equity and expand market reach, yet consumer responses to these collaborations in digital spaces remain fragmented and difficult to predict. This study analyzes the distribution of consumer sentiment, identifies key actors in interaction networks, and explores the extent to which Twitter-based data can complement the evaluation of fragrance co-branding strategy. Using an exploratory social media analytics approach grounded in Digital Public Sphere theory and Social Network Theory, this study integrates Social Network Analysis with six computational modules, wordcloud analysis, sentiment analysis, text network analysis, emotion analysis, trend analysis, and zero-shot classification, applied to 300 public tweets collected via the SocialX platform during 1–12 January 2026 using fragrance and brand collaboration keywords. Results show that public discourse was lexically dominated by neutral sentiment (88%), while zero-shot classification of the same corpus yielded a positive-leaning distribution (82.33%); these are interpreted as two distinct constructs, evaluative polarity versus semantic stance, alongside a Sentiment Index of +0.28 and a dominant happy-emotion classification (92%). Network analysis identified a small number of actors occupying central or bridging positions in information dissemination, and trend analysis detected two major activity peaks on January 1–2, 2026, coinciding with the New Year transition. These findings offer theoretical implications for applying Digital Public Sphere and Social Network Theory jointly to fragrance co-branding discourse, and practical implications for brand managers seeking to monitor how collaboration discourse is expressed and circulates online.

Keywords: Co-branding, Social Network Analysis, Sentiment Analysis, Digital Marketing, Consumer Sentiment, Social Media Analytics

1 Introduction

In the past few decades, the global fragrance market has grown to a considerable extent and by 2030 it is expected to reach a market value of more than USD 70 billion

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[1]. In such extensive competition, fragrance companies are not only competing in terms of product quality but also by constructing of identity and management of consumer's perception [2]. Co-branding is a marketing technique that has come into focus in today's marketing world. Co-branding is business joint venture between two or more brands to develop a product or campaign which allows the development of complementary brand equity [3]. Although brand collaborations can generate synergy for the brand that are felt by consumers, there is a disconnect between that ideal scenario and what happens in the market in response to fragrance co-branding, as the market is unpredictable and responses are often fragmented. Some brand collaborations bring in confusing brand values into consumer's brain [4]. Yet, it is urgent to create knowledge on the creation and growth of a consumer's sentiment in the fragrance segment towards co-branding in a digital environment.

The previous research has laid the foundations of key concepts such as understanding of co-branding dynamics and consumer behaviour in the digital world. The results of the Washburn et al. study, which revealed that brand alliances can improve consumers' product evaluations, especially when the brand alliances are well aligned between the brands of the partnership, is conceptually consistent with recent research on brand fit and brand alliance effects [5]. In the digital environment, social media has become an important platform for marketing and consumer engagement and brands have gained more visibility and reach through the use of influencers, and running campaigns online [6]. For instance, several studies have identified the potentials of X/Twitter to be used in public discussion where it facilitates real-time sharing and interaction. Because of the dynamic nature of Twitter's networks, the most central and most engaged users with respect to topic networks tend to be the ones who can sustain and facilitate the flow of information, and the more peripheral, more relevant to topic users are more sensitive to topic relevance and serve to spread the information more widely [7]. Many studies also show that the elements of retweeting, commenting and hashtag use of Twitter can be used to convey complex public opinion [8]. The emotional bond also applies to the sense of authenticity and a way of expression, as luxury brands are also becoming a part of sustainability and contemporary consumer values, enriching the symbolic fabric luxury fragrances present to consumers [9]. This implies that symbolic and emotional attributes will shift in cultural and generational change, and consequently, it is a significant marketing approach of luxury perfumery [10]. A number of other models are related to SNA which have already been successfully applied to the problem of information dissemination in complex online social hypernetworks, such as those proposed in [11].

There are a number of gaps in knowledge, however, that are not being addressed. First, while some of the co-branding studies have been carried out on general product categories (electronic products, food and beverages), the fragrance industry, which is characterized by a symbolic complexity, has not been sufficiently studied as an object of digital co-branding research [12]. Second, research integrating SNA and Twitter sentiment analysis to assess brand collaboration is still quite limited, and the understanding of how sentiment flows among actors of the social network is limited. Sentiment analysis of Indonesian-language social media text is further complicated by code-mixing and code-switching patterns common in informal online discourse [13].

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Third, past research tends to focus on a single platform (for instance, Instagram), and is platform-centric in nature rather than considering the utility of public conversation on X/Twitter as a way to complement and augment our understanding of the effectiveness of marketing campaigns. The following methodological limitations provide an incomplete picture of consumer perception landscape in the context of co-branding fragrance in 2.0 social media age.

The novelty of this study lies in combining two analytical lenses that have typically been applied in isolation: Natural Language Processing (NLP)-based sentiment and affect analysis, and Social Network Analysis (SNA), integrated under the Digital Public Sphere framework and Social Network Theory (Granovetter, 1973) that ground this research throughout. Brand equity considerations inform the interpretive framing of results, particularly in explaining why symbolic and sensory associations with fragrance brands may register as affectively positive even when explicit sentiment remains neutral, but they are treated as a supporting lens rather than a third co-equal theoretical pillar. The current study thus makes two contributions: theoretical (extending the joint application of Digital Public Sphere theory and Social Network Theory to the fragrance co-branding domain) and practical (a data-informed framework brand managers can use to monitor how collaboration discourse is expressed and circulates online).

Based on the foregoing, this research aims to: (1) examine the distribution and temporal trends of consumer sentiment toward perfume co-branding discourse on X/Twitter; (2) identify key actors and interaction patterns within the Twitter social network and their relationship to sentiment propagation; and (3) explore the extent to which Twitter-based sentiment patterns and network structures can complement, rather than substitute for, the evaluation of perfume co-branding strategy.

2 Methods

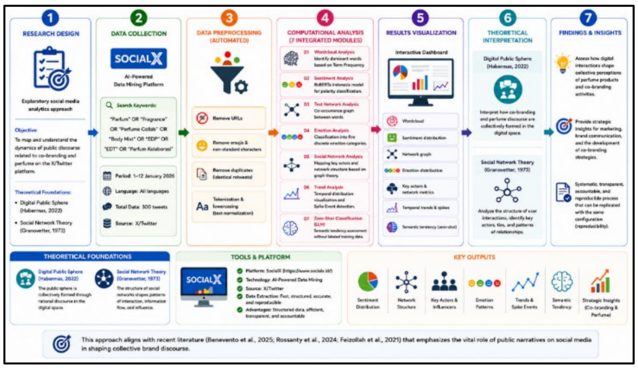

Fig. 1. Research Methodology Framework. Source: Compiled by the author (2026).

This study uses exploratory social media analytics design and de-scriptive-quantitative orientation along with seven computer modules of analysis. This method was chosen because of its ability to capture the interactions between citizens in the

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public sphere around co-branding perfume, both structurally, through the social network (X/Twitter), and semantically, through the attitudes of the consumers. However, exploratory design is most appropriate for studies that seek to discover emergent patterns in large-scale, unstructured social media data without categorical constraints and because visualization plays a critical role in illustrating more complex human mobility patterns or sentiment trends that might arise from large social media datasets, it can reveal salient structures and relationships that would otherwise remain less obvious [14]. From a theoretical perspective, the current research is grounded in two main theoretical frameworks: The Digital Public Sphere that posits that digital public discourse is considered as a rational space of collective perception construction [15]; and the Social Network Theory that states that social network structures affect inter-action patterns, information flows and inter-actor influence. By combining these two theoretical lenses, the processes of both expression and dissemination through digital social structures can be explored simultaneously, a duality that was not possible when looking at either lens alone in previous single-method studies [16].

Data was collected using SocialX AI-Powered Data Min-ing platform (https://www.socialx.id/) which is a social media analytics tool that can systematically and quickly crawl and extract public data from X/Twitter with high accuracy and reproducibility. A dedicated data mining platform guarantees the extraction of structured data, reducing the risk of manual extraction errors and improving the replicability of the process [17], [18]. Data gathered for this period were from 1-12 January 2026 with the following keyword combinations: "Parfum" OR "Fragrance" OR "Perfume Collab" OR "Body Mist" OR "EDP" OR "EDT" OR "Parfum Kolaborasi". Following the common practice in social media keyword-based sampling, the keywords used were created using Boolean OR which is expected to increase the re-call of the discourse in both Indonesian and English that are related to fragrance. No language barriers were imposed on data collection (all languages) to allow for cross-cultural data inclusivity and to capture the multilingual nature of the discourse on fragrance on Twitter, as previously reported as a topic community of the global scale [19]. The main corpus of the tweets was successfully retrieved from the X/Twitter platform and totalled 300 tweets. This 12-day window was selected as an exploratory snapshot of early-year fragrance discourse rather than as a basis for long-term generalization; the implications of this choice for interpreting the findings are discussed in the Limitations section.

All the data was first automatically pre-processed by the SocialX system, including the removal of URLs with no semantic value, the removal of emojis and non-standard characters that may affect text classification processes, the removal of duplicate entries, especially if it is identical retweets which could lead to frequency bias, and tokenization and the lowercasing of the text; as part of text normalization, in order to standardize the lexical forms [20]. These are the typical pre-processing steps that are followed in text mining from social media, as discussed in various best practices in text mining [21]. Before computational linguistic analysis, this pre-processed data set was then checked for completeness, and all 300 data were found to be analytically valid data to be used.

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The analysis of the data was performed using 7 integrated computational modules of the SocialX platform. To get a first impression of the thematic landscape of the tweets, the most dominant words in the tweet corpus was determined using the Term Frequency (TF) via Wordcloud Analysis [22]. Second, Sentiment Analysis was performed using SocialX's built-in sentiment classification module, which classifies each tweet into positive, neutral, or negative polarity categories. This module was used as provided by the platform; its underlying model architecture is not independently documented by SocialX and is therefore not specified here beyond the classification output it returns. Third, Text Network Analysis was used to construct a word co-occurrence graph (G = V, E), in which nodes represent individual words and edges represent their co-occurrence within the same tweet, enabling the identification of semantic clusters and conceptual linkages within the fragrance co-branding discourse [23],[24]. Fourth, Emotion Analysis was applied to classify tweet content into five discrete emotional categories there's happy, sadness, anger, fear, and love to providing a more granular understanding of the affective dimensions of consumer responses beyond binary sentiment polarity [25]. No independent human-coded validation subsample was used to verify emotion classifications, particularly for non-Indonesian content; this is addressed further in the Limitations section.

Fifth, Social Network Analysis (SNA) was conducted by modeling Twitter interaction data as a directed graph G = (V, E), where nodes (V) represent individual users and edges (E) represent directional interactions including mentions, replies, and retweets. Key network metrics computed included degree centrality, betweenness centrality, closeness centrality, network density, and community modularity, following standard SNA methodological conventions as established by Wasserman and Faust [26],[27]. Within this study, degree centrality was used to identify highly connected actors who received a disproportionate share of mentions, replies, and retweets, while betweenness centrality was used to identify bridge actors whose position between community clusters allowed them to facilitate information flow across otherwise separate groups. Node size and cluster position in the SocialX visualization were used as a visual proxy for these two centrality measures rather than as independently reported numerical scores; this operational basis for identifying "influential" actors is treated as indicative of relative position within the observed network, not as a validated or externally calibrated measure of real-world influence [28]. Sixth, Trend Analysis was used to visualize the temporal distribution of tweet volumes across the observation period and to detect spike events defined as statistically significant deviations from the seven-day moving average baseline that indicate moments of heightened public attention toward specific co-branding discourse topics [29]. Seventh, Zero-Shot Classification based on Large Language Models (LLMs) was applied to assess the semantic tendencies of tweets without requiring labeled training data, enabling flexible thematic categorization that adapts to the specific contextual dimensions of fragrance co-branding discourse as they organically emerge from the data [30].

All analytical outputs were visualized through the SocialX interactive dashboard, encompassing wordcloud representations, sentiment distributions, network graphs, emotion distributions, key actor metrics, temporal trends, and semantic tendencies. From a research ethics standpoint, all data constitute content published openly by

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users on X/Twitter, collected solely for academic purposes and consistent with the platform's publicly available data usage policies, with no personally sensitive information retained beyond public usernames.

3 Results and Discussion

3.1 Data Overview

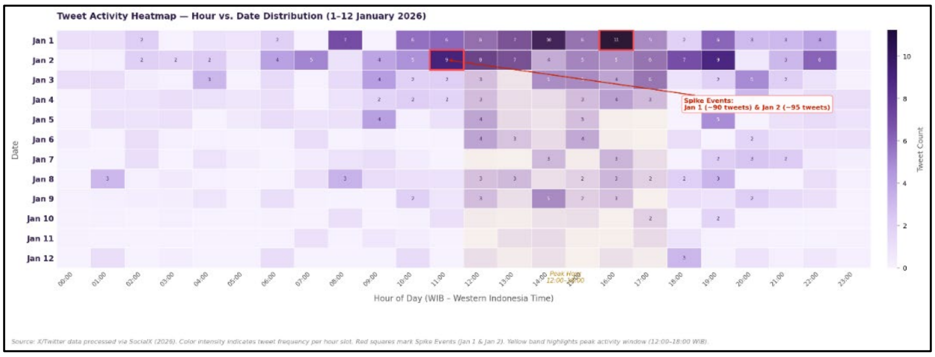

Fig. 2. Tweet Activity Heatmap: Hour vs. Date Distribution (January 1-12, 2026). Source: X/Twitter data processed via SocialX (2026).

The total number of the tweets used in this study was 300 which were collected by data mining process via the platform of SocialX. The data was collected from X/Twitter platform, and the time span of observation was 1-12 January 2026, which is related to the discourse of perfume and co-branding strategies. The data includes social media metadata, like the timestamp of each tweet; user metadata, including who is talking and who is talking to whom; and social interactions, including retweets, mentions and replies. For context on users' engagement, the number of likes, reposts, and quotes are also included. Figure 2 shows a summary of the dataset

The share of tweet activity was highly uneven across time during the study. The most of conversational activity was observed on the first two days of the observation (on January 2, 2026 the number of tweets was about 95, and on January 1, 2026 was about 90). Combined, these two dates made up over 61.7% of all the data, indicating that the dataset is strongly event-sensitive rather than reflective of steady-state discourse. The observed patterns are therefore best read as a response to a specific temporal trigger, the New Year transition, rather than as a stable baseline for everyday perfume co-branding conversation. The high intensity in the first part of January suggests a powerful digital push, either as a result of New Year promotions or the introduction of special edition perfume offers, or perhaps co-branding promotions. After this, the number of tweets significantly decreased from January 3 to 5 (-240 tweets), increased slightly on January 8 (+30 tweets) and then returned to low levels between January 10 and 12 (6-11 tweets).

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A Tweet Activity Heatmap (Hour vs. Date) was used to see how the tweets were distributed by hour and observation date. The heat map (Figure 2) shows that the most active conversation was around 12:00-18:00 WIB (Western Indonesian Time), with darker-coloured cells in the midday-to-afternoon time slots. The peak of the activity occurred at 18:00 WIB on January 1 with 11 tweets per hour, and at 11:00 WIB on January 2 with 9 tweets per hour. This pattern reveals that Twitter's users who partici-pate in per-fume and co-branding conversations are more active during times of greater digital connectivity.

3.2 Wordcloud Analysis

Fig. 3. Wordcloud Analysis: Word Frequency Distribution in Fragrance Discourse (January 1-12, 2026). Source: SocialX (2026).

To find the words that occurred most frequently in the whole set of 300 tweets, Wordcloud Analysis was performed (see Figure 3). Analysis results indicate that the most common words are "parfum", "edp" (Eau de Parfum), "perfume", "fra-grance", "body" and "mist". Because those terms of the technical nature of perfumeries show that the discussions on X/Twitter during the observation period were related to sub-stance, to discussions of perfumes and not to social conversation in general.

The wordcloud also contained in-dividual brand terminology like "sauvage," "bur-berry," "dior" and the name "ralph" (as in Ralph Lauren) and "elysees." These brand-identifiable terms each appeared at frequencies of roughly 6–8% of the corpus ("ralph"/"lauren" and "burberry" at 5.81–8.14%, "dior" at 8.14%, "sauvage" at 6.98%), confirming that specific brand references are present in the discourse but at a frequency too low for reliable brand-by-brand comparison without a larger or brand-stratified sample. This study reports discourse patterns at the aggregate category level and does not compare the relative performance of individual brand collaborations; the frequencies above are reported descriptively to characterize the corpus, not as a basis for ranking brand success. These results indicate that most public discussion was not only of perfume in a categorical sense, but also in reference to the well-known brands which are typically large players in the premium perfume co-branding market. The

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words “collection” and “new” are big, indicating consumer excitement towards new releases or collections at the beginning of 2026.

Words such as "vanilla," "fruity," "sweet," "mint," "scent" and "wangi" also provide sensory experience dimension. This indicates that con-sumer conversation on X/Twitter was shifting beyond transactional and information-based to expressing and sensory. Consumers were vividly describing the aroma attributes of the product they discussed. This discovery con-firms that there is an affective di-mension in consumer digital discourse with per-fume products.

3.3 Text Network Analysis

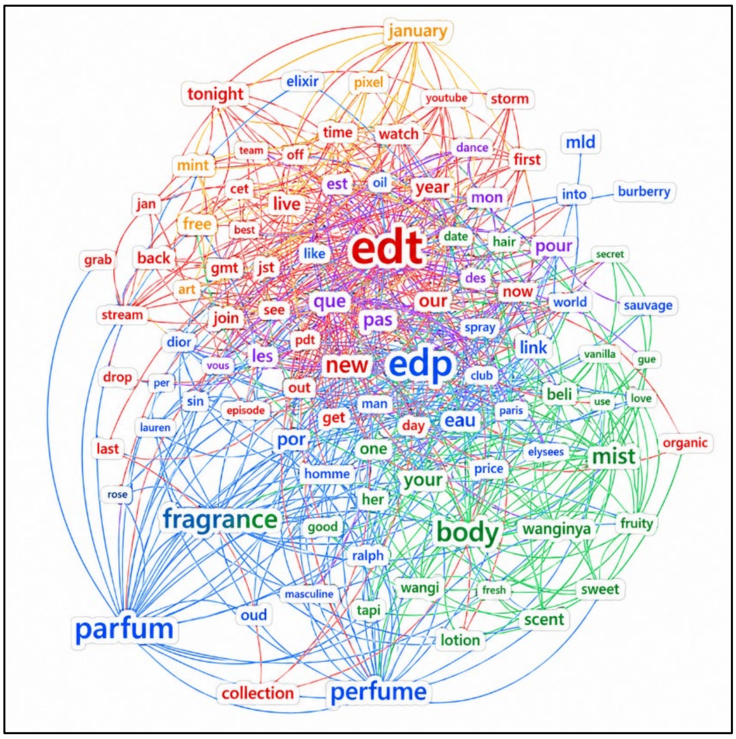

Fig. 4. Text Network Analysis: Word Co-Occurrence Map in Fragrance Discourse.
Source: SocialX (2026).

Developed using the 300 tweets, the graph is a Text Network Analysis (TNA) which shows the co-occurrence relationships between words (Figure 4). The analysis results show that the nodes with highest size that reflect the highest centrality in the word network are "edt" (Eau de Toilette), "edp" (Eau de Parfum), "parfum", "per-fume", "fragrance", "body", and "mist". These terms represent the main discourse nodes, on which most of the conversations in the network are based, and indicate that

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the perfume products' type and format is the main topic that connects many sub-discourses.

A graph visualization was used to extract four different clusters of meaning. The green cluster is found in the bottom right of the graph and includes words like "body," “mist,” “wanginya,” “fruity,” “sweet,” “scent,” “lotion,” and other words that represent a sub-discourse on body mist, sensory experience. The left side of the cluster, by contrast, has a red cluster of words such as “fragrance,” “parfum,” “oud,” “masculine,” and “ralph,” related to men's fragrance and high quality men's “per-fume.”

The middle portion of the graph shows that the two technical terms “edt” and “edp” have a very dense network of connections to nearly all other clusters in the graph, indicating that these two technical terms are semantic bridges which link various sub-topics of the conversations about perfume. The conversations throughout the observation period are dominated by a discourse of new product launches at the start of the year, as signaled by other words that were highly associated with each other, such as "new", "january", "collection", "pour", and "eau". The results of the text network analysis confirm the multi-dimensionality of the co-branding discourse in the Twitter space, and the presence of those dimensions: the technical aspects of the perfume, the brand identity, the senso-rial aspects, and the temporal aspects of perfumes.

3.4 Sentiment Analysis

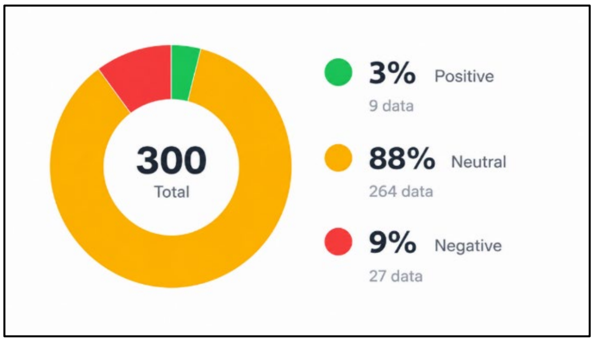

Fig. 5. Sentiment Analysis Distribution of the 300-Tweet Corpus. Source: SocialX (2026).

All 300 tweets included in the research corpus were analyzed using SocialX's built-in sentiment classification module. The classification results indicated that neutral tweets (264, 88%) were the most common, negative tweets (27, 9%), and positive tweets (9, 3%) were the least common (Figure 5). The dominance of neutral sentiment indicates that most tweets did not contain explicit evaluative expressions of approval or rejection. In the context of perfume co-branding discourse, this suggests that users primarily used X/Twitter to share information, mention products, describe fragrance attributes, or refer to new collections rather than to express direct positive or negative judgments. At the lexical sentiment level, consumer perception cannot therefore be described as predominantly positive; the discourse is better characterized as largely informational and neutral, with limited explicit positive sentiment.

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This overall sentiment, neutral (88%) needs to be put into context of the type of conversation that is happening on Twitter, as this is often used for the dissemination of information, product recommendations and the dissemination of education related content about perfumes, including snippets of product reviews, price and new collections announcements. In spite of the small number of negative sentiment (9% or 27 tweets), it is analytically significant, as it could be the voice of consumers and indicate some dissatisfaction about prices or criticism of specific co-branding strategies that did not seem to resonate with consumers' perceptions. The other side to that is that the proportion of positive sentiment is quite small (3%, 9 tweets) making that the sentiment of "explicit and semantically confirmed expressions of appreciation or enthusiasm" was relatively uncommon in this discourse.

This sentiment distribution pat-tern is very important in the perfume co-branding study. Overall, the results show high neutral sentiment levels, suggesting that the brands engaging in collaborative strategies have not yet been able to direct consumer conversations towards a more positive and emotion-arousing sentiment, which is a paradox to the goal of co-branding as a strategy to enhance the brands' equity through emotional connections (Keller, 2013). The sentiment analysis layer gives the interpretive understanding that is used in the emotion analysis and zero-shot classification layers explained in the following sections.

3.5 Emotion Analysis

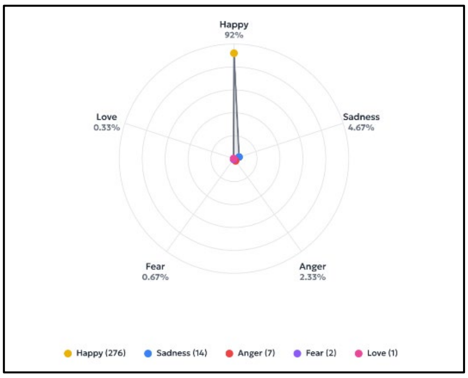

Fig. 6. Emotion Analysis Distribution of the 300-Tweet Corpus. Source: SocialX (2026).

To gain a closer look into the affective aspects of perfume co-branding discourse, Emotion Analysis was carried out. Within the five emotion categories, the classification re-sults showed a very high number of Happy emotion tweets (276 tweets which is 92% of the total number of tweets). Sadness ranked second with 14 tweets (4.67%), followed by Anger with 7 tweets (2.33%), Fear with 2 tweets (0.67%), and Love with 1 tweet (0.33%). A radar diagram is used to see this distribution visually, and to confirm the absolute dominance of the happy emotion dimension in the conversational network (Figure 6).

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The sentiment analysis results showed that 88% of the tweets were neutral in nature, while at 92% the happy emotion dominated, this seems contradictory. The apparent contradiction can be understood by the methodo-logical differences between the two analyses: sentiment analysis is about the evaluative polarity of the entire content, whereas emotion analysis is concerned with the latent affective tone of content that may be lexically neutral but emotionally positive. In other words, lots of tweets that were neutral regarding the sentiment were discovered to have a tone of happiness or enthusiasm which does not always map into explicit evaluative language.

The overall ratio of the negative emotions, anger (2.33%), fear (0.67%) and sadness (4.67%), is very low and suggests that during the observation period, the affective ecosystem of the discourse on perfume co-branding on Twitter leaned toward positive and stable affective expression. A distribution this concentrated in a single emotion category is nonetheless higher than what is typically reported for open social media discourse, and part of this concentration likely reflects classifier behavior on a corpus that, as noted in the Limitations section, includes non-Indonesian tweets outside the platform's primary processing strengths; without a manually annotated validation subsample, the exact share attributable to genuine affective positivity versus model bias toward a default majority class cannot be precisely disentangled. With that caveat in mind, this discovery is still informative from the Digital Public Sphere point of view (Habermas, 2022), as the digital space functions as an arena in which a collective perception of perfume products and brand collaboration activities is formed, and the observed skew toward happiness is a signal, rather than a confirmed measure, of a more favorable reception climate for co-branding strategies.

4 Social Network Analysis

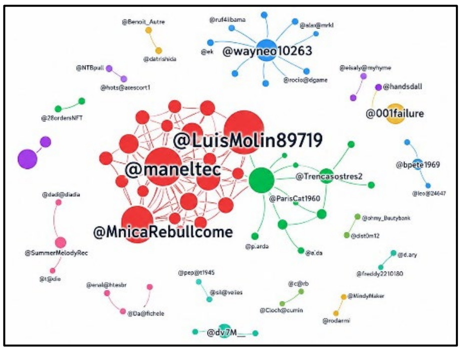

Fig. 7. Fig. 8. Social Network Analysis: Mention Interaction Network in Fragrance Discourse. Source: SocialX (2026).

A social network analysis (SNA) of 300 tweets over January 1 to 12, 2026 created a directed graph of the interaction patterns of users of X/Twitter when they are talking about co-branding in perfumes. The three biggest actors with the largest node sizes are @LluisMolin89719, @MnicaRebullCome, and @maneltec located in the red clus-

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ter in the middle of the graph. Their high degree centrality scores indicate that these accounts had a large node size so they are most likely to be reached by mentions, replies, and retweets. The complex and multi-layered interactions between them suggest deep and active cross-references between the three nodes and confirm the idea that they are not just part of the stream of information but are active amplifiers of perfume co-branding content.

The visualization also provides a few community clusters that differ in structure and are different discursive sub-communities outside the dominant red cluster. The blue cluster appears to have a more linear interaction pattern and is led by @wayne010263 as a local hub, the green cluster includes @Trencasostres2 and @ParisCat1960 and has more linear interaction patterns with the main cluster while the yellow and purple clusters have few connections with the main clusters. Such cluster diversity is evidence of high community modularity, which means that users are closer to each other in their communities than between communities.

Betweenness centrality indicates that both @maneltec and @Trencasostres2 are bridge actors between the red and green clusters, and play an important role in the flow of information in and out of these communities. Other peripheral nodes, however, are not as effective as amplifying nodes, such as @SummerMelodyRec, @dv_7M, and @MiranyMaker. The patterns that emerge are consistent with the Social Network Theory (Granovetter, 1973) that proposes that network strength is not represented by the number of members in the network, but by the strategic position of some actors in the network that controls the in-formation flow inside the digital discourse system. These centrality-based distinctions were derived from relative node size and cluster position within the SocialX visualization rather than from independently reported numerical thresholds or a validation procedure; the identification of "influential" or "bridge" actors here should therefore be read as indicative of their position within this specific observed network, not as a precisely calibrated or externally validated measure of influence.

4.1 Trend Analysis

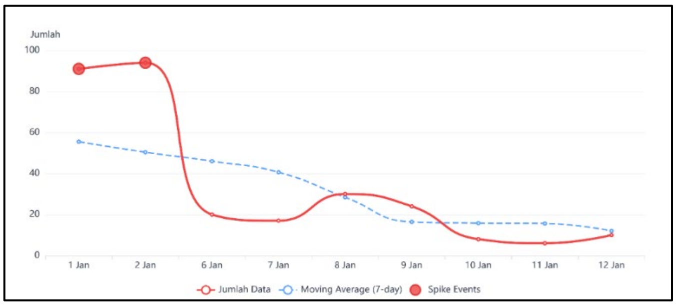

Fig. 9. Trend Analysis: Daily Tweet Volume and 7-Day Moving Average (January 1–12, 2026). Source: SocialX (2026).

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First, a temporal trend analysis was undertaken to identify temporal patterns in the distribution of the number of tweets over the time period under observation (from the 1st to the 12th January 2026) in order to single out periods of conversation activity, known as spike events. A line graph was used to visualize the number of tweets per day and the 7-day moving average, and it was determined that there were two major spike events, one at January 1 2026 with ±90 tweets and the other at January 2 2026 with ±95 tweets. These two dates also coincided with the start of a new year, so that the "New Year moment" was an important impetus for an increase of public discourse on per-fume and co-branding on X/Twitter.

The graph indicates that the peak activity was on January 1-2, followed by a steady downward trend after that day with the number of tweets per day rapidly dropping to approximately 17-20 tweets per day on January 6. There was a slight uptick on January 8 (+/- 30 tweets) and then another drops off to very low levels on January 10-12 (6-11 tweets). The 7-day moving average is slightly flat, decreasing from about 54 tweets on day one of the trend to 11 on day 7 of the trend. The pattern seems to be cyclic, meaning that public awareness towards the topic of co-branding perfume on Twitter is strongly related to specific moments and not to constant moments.

The data from the hourly tweet activity heatmap (WIB) allows the trend analysis to be given an intra-day temporal dimension. The heatmap indicates that the high activity of tweets was observed in the period of 12:00 – 18:00 WIB (western Indonesia time) as the main peak hours for the observation period. The most active hour during 1st January was 18:00 - 19:00 WIB (with 11 tweets) while on 2nd January, the highest hourly activity was at 11:00 WIB (11 tweets). Based on the results, the most optimal period of time for the co-branding campaign in perfumes using social media is the midday to afternoon in the Western Indonesian Time zone, and the best time using celebratory moments or seasonality and year end transition as a trigger for public conversation is the midday to afternoon period in the Western Indonesian Time zone. Because both spike events coincide with the New Year transition, the observed rise in tweet volume is better read as a response to seasonal and calendar-driven attention rather than as direct evidence of co-branding campaign effectiveness.

4.2 Zero-Shot Classification

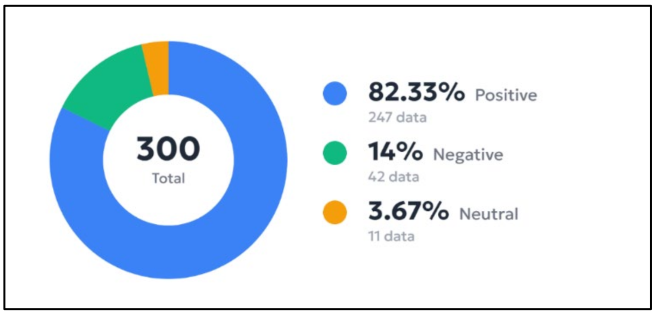

Fig. 10. Zero-Shot Classification Distribution of the 300-Tweet Corpus (January 1–12, 2026). Source: SocialX (2026).

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To enable flexible thematic categorization of specific aspects within perfume co-branding discourse, a zero-shot classification based on a LLM (Large Language Model) was applied to classify 300 tweets without the need to have labelled training data. The classification results showed an extremely skewed distribution with 82.33% (247 data points) classified as Positive, 14% (42 data points) classified as Negative and 3.67% (11 data points) as Neutral. The result of the distribution is very much skewed from the sentiment analysis results, which showed a majority at 88% of neutral sentiment. Any differences between the zero-shot classification and the sentiment analysis are not contradictory, but rather indicate a conceptually different measure. The platform's sentiment classification module identifies sentiment polarity lexically and evaluatively on the basis of explicit opinion expressions in the text, while LLM-based zero-shot classification can identify more subtle semantic sentiment tendencies, such as implicit tone, contextual framing, and layered meaning that may not surface as explicit polarity.

In sum, these zero-shot classification results offer another analytical layer on the tendencies of public discourse about perfume co-branding on Twitter. Rather than resolving the discrepancy with the sentiment analysis finding, this layer indicates that the corpus carries an implicit positive-leaning stance beneath its predominantly neutral surface phrasing. The two findings are treated in this study as complementary constructs rather than a single settled verdict on consumer sentiment: the platform's sentiment classification module describes how consumers state things, while zero-shot classification describes the direction the content leans toward when read for stance. The 82.33% figure is therefore reported as a semantic-stance indicator, not as a correction of or replacement for the neutral-dominant sentiment finding.

4.3 Sentiment Index Analysis

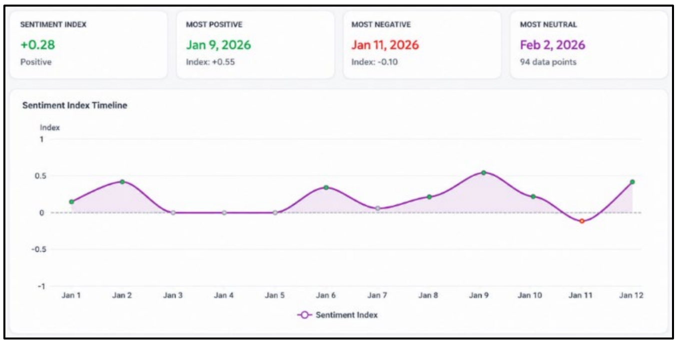

Fig. 11. Sentiment Index Analysis: Daily Sentiment Fluctuation Timeline (January 1–12, 2026). Source: SocialX (2026).

Sentiment Index Analysis was also conducted to determine the overall direction of the discourse of the co-branding perfume in aggregate during the observation period (1 January-12 January 2026) on the X/Twitter platform. The overall Sentiment Index value was in the Positive range and registered at +0.28 on the SocialX dashboard,

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based on the results shown. This index value was derived by adding together the sentiment weights of all 300 tweets observed over the time period and aggregating them together, with a positive value indicating that the overall sentiment of public discourse on Twitter about perfume co-branding was positive, or favourable, towards the perfume brands. The value of +0.28 is in the moderate positive region but not the maximum value of +1. This is a significant finding because it represents that there was no dominant negative sentiment within the digital discourse ecosystem that was threatening the brand during this time.

The Sentiment Index Timeline visualization shows the fluctuations in value of the index on a day-to-day basis, and also shows a wave-like pattern, which indicates the change in quality of sentiment over time. The peak of positive sentiment was on the 9th of January 2026, when the index reached +0.55. The minimum index value that ever moved into the negative region was on January 11, 2026 at the index value of -0.10, the lowest in terms of sentiment quality. The day with the highest data volume was recorded as January 2, 2026, with 94 tweets, but an index value of only about +0.38, indicating that, while high volume of conversation does not necessarily equate to high sentiment quality, it can. The pattern is suggesting a dissociation between the number and the sentiment of the discourse, with the highest numbers of tweets not necessarily coinciding with the highest positive sentiment.

Overall, the Sentiment Index Timeline curve appears to oscillate with three positive peaks (January 2 (+0.38), January 6 (+0.32), and January 9 (+0.55)) and three troughs, or valleys, touching or near zero (January 3-5, and January 7-8). This oscillation suggests that public sentiment about co-branding discourse was never constant, but was subject to certain external factors, such as viral content and product announcements, or celebratory moments, which periodically pushed sentiment quality up and then down again. This discovery supports the view that the co-branding of perfumes on social media is not a one-off, but must be supported by a series of carefully planned and timed content stimuli to help maintain positive sentiment momentum over time within the perfume consumer community, on Twitter, in particular.

5 Conclusion

This study finds that public discourse on perfume products and co-branding activity on X/Twitter during 1–12 January 2026 was predominantly neutral in explicit lexical sentiment (88%), alongside a positive-leaning semantic and affective tendency indicated by zero-shot classification (82.33%), emotion analysis (92% happy), and the Sentiment Index (+0.28). These findings should not be read as evidence that consumer perception was uniformly positive; rather, the discourse was largely informational and descriptive on the surface, while carrying favorable associations related to fragrance, sensory experience, and new product collections. Because the observation window coincided with the New Year transition and spans only twelve days, these patterns are best interpreted as a snapshot of a specific and atypical calendar moment rather than a stable baseline for perfume co-branding sentiment.

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Read together through the Digital Public Sphere and Social Network Theory frameworks that ground this study, the seven analytical modules describe a single underlying process rather than seven separate outputs: sentiment, emotion, zero-shot classification, and the Sentiment Index jointly characterize what is being said and how positively or neutrally it is framed, while wordcloud, text network, and social network analysis show how that framing circulates and through which actors it is amplified or bridged across community clusters, with trend analysis marking the temporal moments at which these two processes intensify together.

Social Network Analysis further shows that a small number of accounts occupied central or bridging positions within the observed interaction network, based on relative node position rather than independently validated centrality scores (see Methods). These actors likely contributed to the circulation of co-branding discourse within and across community clusters; their influence should be understood as visibility within this specific dataset, not as demonstrated influence on purchasing behavior or broader market perception.

Overall, this study demonstrates that Twitter-based data can complement, rather than substitute for, the evaluation of fragrance co-branding strategy. It is important to note that this study did not measure sales performance, purchase intention, brand awareness, or customer loyalty, and the discourse patterns identified here should not be read as direct evidence of commercial effectiveness; they are better understood as evidence of digital discourse resonance during a specific observation period.

6 Limitations and Recommendations for Further Research

While this study has yielded valuable insights, several limitations should be acknowledged. First, only 300 tweets from a 12-day period (1–12 January 2026) were analyzed, and this period coincided with the New Year transition; the observed tweet volume, sentiment pattern, and emotion distribution may reflect seasonal and celebratory online behavior rather than steady-state discourse, so the findings cannot be generalized to long-term consumer sentiment toward perfume co-branding.

Second, this study focused on a single platform, X/Twitter, which has unique demographic and communication characteristics not necessarily shared with Instagram, TikTok, or YouTube. Relatedly, X/Twitter users who post publicly about perfume represent a self-selected and demographically narrow subset of consumers who skew toward more digitally active and vocal users; this subset does not necessarily correspond to the broader population of actual perfume buyers. The findings should therefore be read as characteristics of public digital conversation, not as a proxy for consumer perception or purchasing populations at large.

Third, because tweets were collected via keyword-based scraping rather than language-filtered collection, the corpus is inherently multilingual, and this is not a marginal artefact: several French function words (e.g., "que," "pas," "pour," "les," "des") each appear in 8–17% of the corpus, alongside Portuguese and English content. The sentiment and emotion classifications used in this study were generated by SocialX's built-in analytical modules, and no manual validation subsample was used to verify

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classification accuracy on non-Indonesian tweets specifically. The reported sentiment and emotion distributions should therefore be read as descriptive of the corpus as processed by the platform, not as a validated measure of true public sentiment across all languages present in the data.

Fourth, this study did not conduct a brand-level breakdown of co-branding conversations; this is a genuine analytical gap rather than a data limitation, since brand-identifiable terms (e.g., "ralph"/"lauren," "burberry," "dior," "sauvage") did surface in the wordcloud and text-network analyses at frequencies of roughly 6–8% of the corpus. The aggregate-level results reported here cannot distinguish between more and less successful individual brand collaborations.

Future work is suggested to be conducted for a longer observation period, with at least 3-6 months beyond the festive seasons; to incorporate other platforms data like Instagram or TikTok; or to use multilingual sentiment analysis model like XLM-RoBERTa to enhance the accuracy of the cross-language content classification. The precise identification of co-branding brands as units of analysis, coupled with the inclusion of qualitative approaches through in-depth interviews, would further contribute to the understanding of the motivations behind the identified sentiment patterns, and at the same time, would give a more precise contribution to the development of perfume co-branding marketing strategies in the digital era.

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