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Sentiment Analysis and Consumer Pain Points Toward Paragon Masstige Brands on Twitter/X

Analisis Sentimen Dan Pain Point Konsumen Terhadap Brand Masstige Paragon Pada Twitter/X

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Abstrak

Media sosial menjadi ruang penting bagi konsumen untuk menyampaikan opini, pengalaman, dan pertimbangan pembelian terhadap produk kecantikan. Penelitian ini bertujuan untuk menganalisis sentimen dan pain point konsumen terhadap brand masstige Paragon pada Twitter/X. Cakupan awal penelitian meliputi lima brand, yaitu Instaperfect, Crystallure, Labore, TAVI, dan Make Over. Namun, Make Over tidak dimasukkan dalam analisis akhir karena kata kunci "make over" dan "makeover" menghasilkan noise yang tinggi akibat penggunaannya sebagai istilah umum dalam bahasa Inggris. Data akhir penelitian terdiri dari 488 komentar dari empat brand, yaitu Instaperfect, Crystallure, Labore, dan TAVI. Penelitian ini menggunakan pendekatan text mining dengan tahapan crawling data, preprocessing, pelabelan sentimen secara manual, klasifikasi menggunakan Naive Bayes melalui Orange Data Mining, evaluasi model, serta pain point analysis. Hasil penelitian menunjukkan bahwa sentimen netral mendominasi sebanyak 368 komentar (75,41%), diikuti sentimen positif sebanyak 103 komentar (21,11%) dan sentimen negatif sebanyak 17 komentar (3,48%). Model Naive Bayes memperoleh nilai accuracy sebesar 0,746, tetapi nilai AUC dan MCC yang rendah menunjukkan bahwa performa klasifikasi masih terbatas karena dominasi komentar netral. Pain point utama yang ditemukan meliputi isu stok, akses, dan transaksi; pemilihan shade dan warna; serta pertimbangan harga, promo, dan value. Dominasi sentimen netral, disertai tingginya kemunculan pain point stok/akses/transaksi, shade/warna, dan harga/promo/value, menunjukkan bahwa banyak percakapan Twitter/X berkaitan dengan pencarian informasi dan pertimbangan pembelian, bukan hanya ekspresi kepuasan atau ketidakpuasan secara eksplisit.

Kata kunci*: Analisis sentiment; Naive Bayes; Twitter/X; pain point; Paragon*

Abstract

Social media has become an important space for consumers to share opinions, experiences, and purchase considerations regarding beauty products. This study aims to analyze consumer sentiment and pain points toward Paragon's masstige brands on Twitter/X. The initial scope of the study included five brands, namely Instaperfect, Crystallure, Labore, TAVI, and Make Over. However, Make Over was excluded from the final analysis because the keywords "make over" and "makeover" generated a high level of noise due to their common use as general English terms. The final dataset consisted of 488 comments from four brands, namely Instaperfect, Crystallure, Labore, and TAVI. This study employed a text mining approach involving data crawling, preprocessing, manual sentiment labeling, Naive Bayes classification using Orange Data Mining, model evaluation, and pain point analysis. The results show that neutral sentiment dominated with 368 comments (75.41%), followed by positive sentiment with 103 comments (21.11%) and negative sentiment with 17 comments (3.48%). The Naive Bayes model achieved an accuracy of 0.746, but the low AUC and MCC values indicate that its classification performance remains limited due to the dominance of neutral comments. The main pain points identified include stock, access, and transaction issues; shade and color selection; and price, promotion, and value considerations. The dominance of neutral sentiment, together with the high occurrence of stock/access/transaction, shade/color, and price/promotion/value pain points, suggests that many Twitter/X conversations were related to information-seeking and purchase consideration rather than explicit expressions of satisfaction or dissatisfaction.

Keywords: Sentiment analysis; Naive Bayes; Twitter/X; pain point; Paragon

INTRODUCTION

The beauty industry in Indonesia continues to grow alongside increasing consumer awareness of self-care, lifestyle changes, and the strengthening role of digital media in shaping market perceptions. This development can be seen in the increasing number of cosmetic industry players in Indonesia. Badan POM recorded that, as of July 2024, there were 1,178 cosmetic industries in Indonesia, around 90% of which were MSMEs. In addition, the high penetration of social media has also strengthened the role of digital spaces in shaping consumer perceptions. DataReportal recorded that Indonesia had around 180 million active social media user identities in 2026, equivalent to 62.9% of the total population. This situation makes it easier for consumers to search for information, compare products, and openly share their usage experiences. In the context of digital marketing, consumer experiences shared through social media can be understood as a form of electronic word of mouth (e-WOM), which influences brand image, trust, and consumer purchase intention (Hennig-Thurau et al., 2004; Sjukun & Yulius, 2023; Arif et al., 2024). Therefore, beauty brands need to understand consumer conversations in digital spaces, because perceptions of products are no longer shaped only by brand claims but also by comments, reviews, recommendations, and experiences shared by consumers.

In this context, Paragon is one of Indonesia's beauty companies that oversees various cosmetic and personal care brands with different characteristics, positioning, and target consumers. Paragon's brand portfolio includes brands such as Wardah, Emina, Make Over, Kahf, Instaperfect, Crystallure, Labore, TAVI, and several other brands. Based on their positioning characteristics and target consumers, this portfolio can be understood as consisting of several brand segments, such as halal, youth, and masstige. This study focuses on the masstige segment, namely brands that combine broad market reach with a perception of prestige or premium value. The initial scope of masstige brands in this study included Make Over, Instaperfect, Crystallure, Labore, and TAVI, based on the concept of masstige in marketing literature, which emphasizes the combination of market accessibility and perceived premium value (Kumar et al., 2020; Mansoor et al., 2024).

The focus on Paragon's masstige brands is relevant because consumers in this category consider not only product functionality but also value, price, brand image, quality, product appearance, and usage experience. In beauty products, these considerations often appear in the form of questions, recommendations, reviews, complaints, promotions, and buying and selling activities on social media. Therefore, consumer conversations about Paragon's masstige brands in digital spaces can provide an overview of how consumers interpret products, compare choices, and express needs or barriers before purchasing.

Social media is one of the relevant data sources for understanding these conversations because it contains opinions that are spontaneous, current, and not always captured in formal surveys. Twitter/X, as a short text-based platform, enables users to directly express experiences, questions, complaints, recommendations, and buying and selling activities. Qi and Shabrina (2023) explain that Twitter is an important data source in sentiment-based research because it provides a space for users to openly express opinions, experiences, and views on a topic. In the context of Paragon's masstige brands, conversations on Twitter/X can be used to examine how consumers discuss products, compare choices, search for information, and express pre-purchase considerations.

In the context of beauty products, consumer comments on social media do not always appear as explicit expressions of satisfaction or dissatisfaction. Many comments instead take the form of questions, information seeking, promotions, buying and selling activities, recommendations, and general discussions. Several national studies on beauty products show that digital consumer data can be used to understand market perceptions and responses to beauty products (WP et al., 2024; Pradhana et al., 2024; Nabila & Putra, 2024). However, comments that appear neutral also need attention because they often contain information needs and pre-purchase considerations, such as questions about shade, price, promotions, suitability for skin type, and product availability.

In relation to this focus, reading general sentiment tendencies still has limitations. Sentiment can provide an initial overview of consumer perceptions, but it does not fully explain the issues underlying the comments. In the context of beauty products, consumer conversations often contain pre-purchase uncertainty, barriers to obtaining products, information needs, and usage experiences that do not always appear as direct complaints. Therefore, this study complements sentiment analysis with pain point analysis so that the issues emerging in consumer conversations can be identified more concretely.

Research on sentiment analysis of beauty products has been conducted across various objects and digital platforms. Berlianti and Hidayat (2024) analyzed sentiment toward beauty products based on Female Daily reviews, Sain et al. (2025) examined sentiment toward Azarine sunscreen on the Shopee marketplace, while Novitasari et al. (2025) analyzed Twitter user sentiment toward skincare using Support Vector Machine. These three studies show that sentiment analysis has been used to read consumer perceptions of beauty products through digital data. However, studies that specifically discuss Paragon brands, especially Paragon’s masstige brand group such as Instaperfect, Crystallure, Labore, and TAVI, remain limited. In addition, based on their research focus, these studies have not explicitly combined sentiment classification with pain point analysis to explain the specific issues underlying consumer conversations.

This gap is important because sentiment analysis only indicates the direction of consumer opinion, but does not explain the concrete issues that shape the conversation. In the context of beauty brands, consumer conversations are not only related to positive or negative evaluations of products, but may also contain information needs, uncertainty, and barriers before purchasing. If the analysis stops at sentiment classification, the more operational issues behind consumer comments risk remaining unidentified. Therefore, this study combines sentiment analysis and pain point analysis to understand opinion patterns while identifying concrete issues in consumer conversations about Paragon’s masstige brands on Twitter/X.

LITERATURE REVIEW

Electronic word of mouth, or e-WOM, is an important concept for understanding consumer conversations in digital spaces. Hennig-Thurau et al. (2004) explain that e-WOM refers to positive or negative statements made by consumers about a product or company and disseminated through internet-based media. In the context of digital marketing, e-WOM can influence brand image, trust, and consumer purchase considerations (Sjukun & Yulius, 2023; Arif et al., 2024). In the beauty industry, e-WOM has become increasingly relevant because consumers often need validation from other users before purchasing products related to personal preferences, skin conditions, skin tone, usage results, and perceived quality. Thus, consumer comments on social media can be read not only as positive or negative opinions, but also as a form of information seeking, experience validation, and pre-purchase consideration.

The concept of masstige is also an important foundation in this study. Masstige is a combination of mass and prestige, referring to a brand strategy that combines broad market reach with perceived premium value. Kumar et al. (2020) explain that masstige marketing is related to brands’ efforts to create prestige appeal while remaining accessible to a wider range of consumers. Mansoor et al. (2024) also emphasize that masstige is related to symbolic motivations and purchase intention toward products that combine prestige appeal with broader market reach. In this study, Paragon brands such as Make Over, Instaperfect, Crystallure, Labore, and TAVI are positioned as masstige brands because they offer a more premium product image, higher communicated quality, and a more aspirational usage experience than ordinary mass beauty products. Therefore, consumers of Paragon's masstige brands consider not only product functionality but also value, price, brand image, quality, product appearance, shade suitability, skin compatibility, and usage experience.

Sentiment analysis is an approach in natural language processing and text mining used to identify and classify tendencies of opinion, evaluation, or subjective emotion in textual data (Ashbaugh & Zhang, 2024). In social media-based research, sentiment analysis is generally used to read users' attitudes toward an object, issue, product, or brand through the classification of positive, negative, and neutral sentiment. Thus, sentiment analysis can be used as an initial approach to understanding the tendency of consumer perceptions in digital conversations.

Naive Bayes is one of the algorithms widely used in text classification because it is suitable for word-feature-based document representations, such as multinomial and Bernoulli approaches (McCallum & Nigam, 1998). This algorithm works based on a probabilistic approach to estimate the class of a text based on the occurrence of certain features. Normawati and Prayogi (2021) applied the Naive Bayes Classifier and confusion matrix in Twitter-based sentiment analysis, while Setyaningsih et al. (2023) used Naive Bayes with Orange Data Mining to analyze public sentiment toward skincare products on Twitter. These findings show that Naive Bayes remains relevant for Indonesian-language sentiment analysis, especially on Twitter data and digital conversations. However, classification results need to be interpreted carefully when the class distribution is imbalanced, because the model may tend to follow the majority class.

Research on sentiment analysis of beauty products has been widely conducted in recent years using various data sources and algorithms. WP et al. (2024) analyzed sentiment in reviews of Somethinc Niacinamide skincare products on Female Daily using the Naive Bayes Classifier, while Pradhana et al. (2024) analyzed sentiment in reviews of Daviena products on Shopee. On social media platforms, Larasati et al. (2024) analyzed sentiment toward moisturizer beauty products on Twitter using the Support Vector Machine algorithm. In addition, Aprilianne et al. (2024) analyzed comment features on the Skintific TikTok account, while Fauziah et al. (2025) analyzed TikTok comment sentiment toward Skintific products. Nabila and Putra (2024) also show that sentiment analysis of viral skincare brands can help map consumer perceptions based on digital conversations. These studies show that digital consumer data, whether from review platforms, e-commerce, or social media, can serve as an important source for reading market responses to beauty products.

In this study, consumer pain points are understood as problems, barriers, needs, or uncertainties that emerge during the processes of information seeking, purchasing, and product use. Salminen et al. (2022) explain that pain point detection can be used to identify consumer messages that contain certain problems or barriers in user-generated content on social media. Similarly, Lee et al. (2023) show that pain point analysis can be used in opinion mining to extract dissatisfaction factors or specific issues from consumer reviews. In the context of beauty products, pain points may relate to product compatibility, color selection, price, product availability, texture, finish, packaging, and the need for reviews before purchasing. Pain points do not always appear as negative complaints; they may also appear in neutral comments in the form of questions, requests for recommendations, or consumer uncertainty about a product. Therefore, pain point analysis is used to complement sentiment analysis because it can explain the issues underlying consumer conversations more concretely.

METHODS

This study uses a descriptive quantitative approach with text mining methods to analyze sentiment and pain points in Twitter/X user conversations about Paragon's masstige brands. The initial scope of the study included five brands, namely Instaperfect, Crystallure, Labore, TAVI, and Make Over. Brand selection was conducted purposively because these five brands represent Paragon's masstige group, which has more premium product characteristics and involves many consumer considerations before purchase, such as value, shade, product availability, and usage experience. However, Make Over was excluded from the final analysis because the keywords

"Make Over" or "makeover" generated a high level of noise and often referred to general English phrases. Therefore, the final analysis used only four brands, namely Instaperfect, Crystallure, Labore, and TAVI. The general research flow is presented in Figure 1.

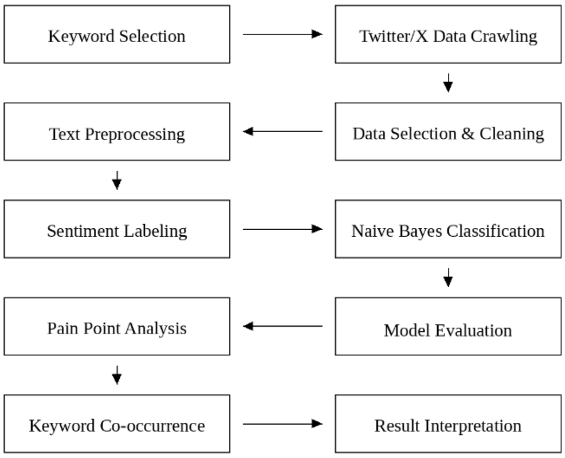

Figure 1. Research Stages

Source: Processed by the author, 2026.

The research data were obtained through Twitter/X crawling on May 29, 2026, using the keywords "Instaperfect," "Crystallure," "Labore," "TAVI," "Make Over," and "makeover." Data collection was not limited to a specific posting period, but included all tweets/comments that could be traced at the time of crawling and matched the research keywords. The sentiment distribution of Twitter/X comments used in this study is presented in Table 1.

Table 1. Sentiment distribution of Twitter/X comments

Sentiment	Number of Comments	Percentage
Neutral	368	75.41%
Positive	103	21.11%
Negative	17	3.48%
Total	488	100%

Source: Processed by the author, 2026.

The preprocessing stage was conducted to prepare textual data before analysis, including case folding, tokenization, stopword removal, and the filtering of words relevant to the context of product conversations. After preprocessing, sentiment labeling was performed manually by the researcher based on predetermined category guidelines. Each comment was labeled as positive, negative, or neutral according to the context of its content, namely whether the comment indicated a favorable evaluation, a complaint or unfavorable experience, or merely contained questions, information, and general conversation without explicit opinion. Ambiguous comments were reviewed by considering the sentence context and keywords appearing in the comments.

Sentiment classification was conducted using a single classification model, namely Naive Bayes, through Orange Data Mining. Model evaluation was performed using stratified 5-fold cross validation to maintain the proportion of sentiment classes in each data split, thereby producing more stable evaluation results on an imbalanced dataset. Model performance was then assessed using several evaluation metrics so that performance could be interpreted more comprehensively, not only based on accuracy. The classification and model evaluation scheme is presented in Figure 2.

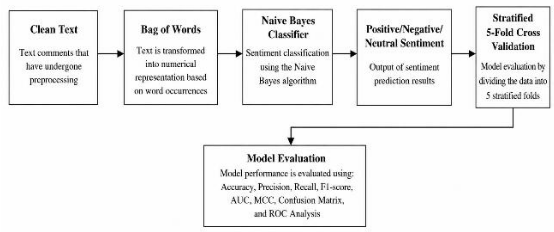

Figure 2. Naive Bayes Classification and Model Evaluation Scheme

Source: Processed by the author, 2026.

In addition to sentiment analysis, this study conducted pain point analysis to identify consumer issues, needs, and barriers that emerged in Twitter/X conversations. Pain point analysis was conducted using a keyword-based tagging approach on the clean text column. The categories used included stock/access/transaction, shade/color, price/promotion/value, skin compatibility/skin type, information/review/recommendation, performance/usage result, texture/finish/comfort, and packaging/usability. Because one comment could contain more than one issue, this analysis was multi-label, so the number of pain point occurrences could exceed the number of comments analyzed.

Keyword co-occurrence analysis was used to examine the relationships between keywords that frequently appeared together in a single comment. This analysis was conducted by extracting important keywords from the clean text, removing irrelevant common words, and then calculating pairs of words that appeared in the same comment. The co-occurrence results were used to strengthen the interpretation of pain points and explain the context of consumer conversations about Paragon's masstige brands.

RESULT AND DISCUSSION

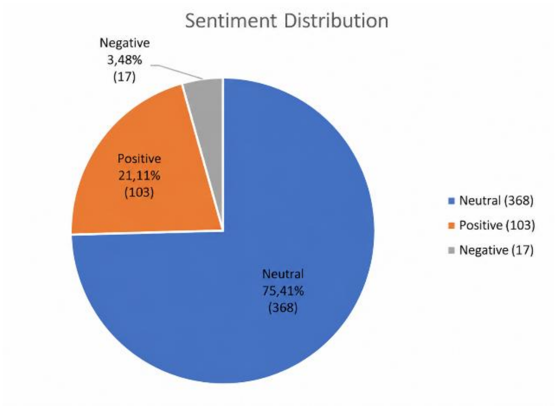

Figure 3. Sentiment Distribution Visualization

Source: Processed by the author, 2026.

Based on Figure 3, Twitter/X user conversations about Paragon's masstige brands were dominated by neutral sentiment. This finding indicates that most comments were not direct evaluations of products, but rather informational interactions, such as questions, recommendation seeking, promotional discussions, product availability inquiries, and buying and selling activities. Therefore, neutral sentiment in this study is not understood as the absence of consumer response, but as an indication of an information-seeking process before purchase.

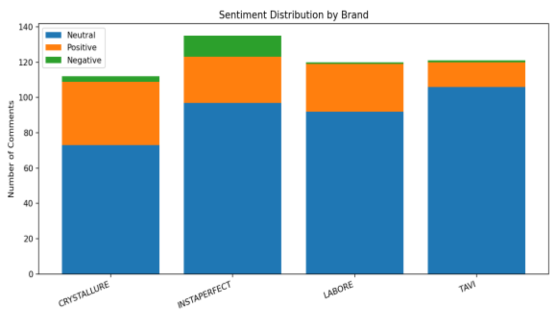

Figure 4. Sentiment Distribution by Brand

Source: Processed by the author, 2026.

Based on Figure 4, the dominance of neutral sentiment was evident across all analyzed brands, but each brand showed different conversational tendencies. Crystallure had relatively more prominent positive sentiment than the other brands, while Instaperfect showed a higher number of negative comments. Meanwhile, Labore and TAVI appeared more often in conversations related to product questions, usage suitability, product availability, and purchase information seeking. These differences show that although the general sentiment pattern tended to be neutral, the conversational context for each brand still had distinct characteristics.

Table 2. Examples of Neutral Comments Containing Information Seeking and Purchase Consideration

Brand	Example of Anonymized Comment	Pain Point Category
Instaperfect	*"Kalau biasanya pakai two way cake Luxcrime Custard, cocoknya pakai cushion Instaperfect shade apa ya?"*	Shade/color; information/review/recommendation
Instaperfect	*"Cushion Instaperfect mesh lagi promo B1G1, tapi masih bingung dengan shade-nya."*	Price/promotion/value; shade/color
Crystallure	*"Ada yang pernah coba Crystallure? Kepo, itu brand Paragon ya ternyata."*	Information/review/recommendation
Crystallure	*"Ada yang pakai Crystallure overnight cream? Mau review-nya."*	Information/review/recommendation
Labore	*"Sunscreen Labore yang acne dan oily protect cocok tidak dipakai sebelum makeup?"*	Skin compatibility/skin type; texture/finish/comfort
Labore	*"Boleh bantu koreksi skincare routine untuk kulit sensitif, bekas jerawat, dan kusam? Mau coba step skincare bagian serum."*	Information/review/recommendation; skin compatibility/skin type
TAVI	*"Ada TAVI lip tint shade Chai?"*	Shade/color; stock/access/transaction
TAVI	*"Ada yang jual TAVI sunscreen yang ada tint-nya dengan harga under?"*	Stock/access/transaction; price/promotion/value

Source: Processed by the author, 2026.

Note: Comments were anonymized by removing account names, handles, and users' personal information.

The example comments in Table 2 show concrete forms of neutral sentiment that appeared in consumer conversations. Neutral comments did not only contain general conversation, but also indicated information needs related to shade, price, promotions, reviews, skin compatibility, product availability, and purchase channels. Thus, neutral comments have analytical value because they can help identify consumer needs and barriers that do not always appear as explicit negative complaints.

Model testing was conducted using the Naive Bayes algorithm with stratified 5-fold cross validation. The dataset used was a combination of all brands so that the number of data points in each class was more adequate for the model training and testing process.

Table 3. Naive Bayes Model Evaluation Results

Metrik	Value
AUC	0,596
CA	0,746
F1-score	0,652
Precision	0,78
Recall	0,746
MCC	0,026

Source: Processed by the author, 2026.

The AUC value of 0.596 indicates that the model's ability to distinguish between sentiment classes remained limited because the value was relatively close to 0.5, indicating performance close to random classification. Meanwhile, the Classification Accuracy value of 0.746 shows that the model was able to classify 74.6% of the data according to the actual labels. However, this accuracy value should be interpreted carefully because the sentiment class distribution was imbalanced. In this dataset, neutral comments dominated with 368 out of 488 comments, so the relatively high accuracy was largely influenced by the model's ability to recognize the majority class.

The Precision value of 0.780 indicates that, in aggregate, the model's predictions appeared relatively precise, but this did not yet show that the model was able to recognize all sentiment classes in a balanced manner. This is reflected in the F1-score of 0.652 and Recall of 0.746, which indicate that the balance between precision and the model's ability to recognize actual data remained at a moderate level and was still influenced by the dominance of the neutral class. In addition, the MCC value of 0.026 shows that the overall classification quality remained very weak when considering the relationship between correct and incorrect predictions across all classes. Thus, although accuracy appeared relatively high, the model was not yet able to classify sentiment evenly across positive, neutral, and negative classes.

Table 4. Confusion Matrix of Naive Bayes Classification Results

Actual \ Predicted	Negative	Neutral	Positive	Total
Negative	0	17	0	17
Neutral	6	362	0	368
Positive	0	101	2	103
Total	6	480	2	488

Source: Processed by the author, 2026.

The confusion matrix clarifies the performance limitations of the Naive Bayes model in this study. The model correctly classified 362 out of 368 neutral comments. However, all 17 negative comments were predicted as neutral, while only 2 out of 103 positive comments were successfully recognized as positive. This finding indicates that the model strongly tended to follow the neutral class as the majority class, so its ability to recognize negative and positive classes remained highly limited.

This tendency is related to the characteristics of the Twitter/X data used in this study. Conversations about Paragon's masstige brands were dominated by neutral comments, particularly those related to transaction activities, product searches, promotions, questions about product availability, and purchase considerations. As a result, the word patterns learned by the model represented the neutral class more than the positive and negative classes. Thus, accuracy cannot be the sole basis for evaluating model performance, because the relatively high accuracy was largely influenced by the model's success in recognizing the majority class.

The ROC Analysis results also show a similar pattern. The ROC value for the negative class was around 0.513, the neutral class around 0.501, and the positive class around 0.586. These values indicate that the model's ability to distinguish each sentiment class was still low to moderate. Although the positive class had the highest ROC value compared with the other classes, the value was still insufficient to indicate strong classification performance. Therefore, Naive Bayes in this study is more appropriately positioned as a baseline model to provide an initial overview of sentiment classification, rather than as a final model with high classification performance.

In addition to sentiment analysis, this study conducted pain point analysis to identify the issues that appeared most frequently in consumer conversations. The pain point results show that the stock/access/transaction category was the largest issue, with 224 occurrences or 45.9% of the total data. This category included comments about ready stock, buying and selling, preloved products, marketplaces, COD, refills, and product availability. This finding shows that Twitter/X is used not only as a space for opinions, but also as a space for transactions and product searches.

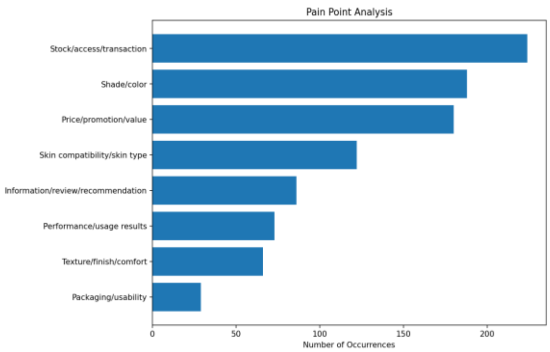

Figure 5. Pain Point Analysis Visualization

Source: Processed by the author, 2026.

Note: Pain point categories are multi-label, so one comment can fall into more than one category.

The second dominant pain point was shade/color, with 188 occurrences. This issue appeared frequently in relation to complexion products, lip products, tints, and blush. Color selection is an important concern because consumers need information about shades, undertones, swatches, and color suitability for specific skin tones. The third pain point was price/promotion/value, with 180 occurrences. Many comments discussed discounts, vouchers, promotions, prices, and considerations of whether a product was worth its benefits. This indicates that masstige beauty consumers are quite sensitive to value.

The skin compatibility/skin type category appeared 122 times and was related to oily skin, dry skin, acne, acne-prone skin, sensitive skin, breakouts, or questions about whether a product was suitable for certain skin conditions. The information/review/recommendation category appeared 86 times, indicating that consumers still needed validation before purchasing. The performance/usage result category appeared 73 times, texture/finish/comfort 66 times, and packaging/usability 29 times. Although their frequencies were lower, these categories remain important because they are directly related to product usage experience.

When viewed by brand, Instaperfect had strong pain points in stock/access/transaction, shade/color, and price/promotion/value. This was related to the many conversations about complexion products such as cushion and loose powder. Complexion products depend heavily on shade selection, so consumers need clearer color guidance and references to usage results across various skin tones.

For Crystallure, the prominent pain points were related to stock/access/transaction, price/promotion/value, and skin compatibility. As a brand with more premium positioning, consumers tended to be more cautious in weighing product benefits against the price offered. Comments containing questions about reviews, usage results, and product suitability are important because they indicate consumers' need for assurance before purchasing.

For Labore, the strongest pain point was related to skin compatibility and skin type. This is consistent with Labore's character as a skincare brand that is widely discussed in the context of sunscreen, moisturizer, and skin care. Consumers often considered whether the product was suitable for oily skin, acne-prone skin, sensitive skin, or could be used as part of skin preparation before makeup.

For TAVI, the most dominant pain points were related to shade/color, price/promotion/value, and stock/access/transaction. The TAVI products most frequently discussed were lip products, blush, tints, and complexion products. Because these products are closely related to color appearance and visual results, consumers needed swatches, shade references, and examples of product results on various skin tones.

After identifying the main pain points for each brand, the analysis continued with keyword co-occurrence analysis to examine the relationships between keywords that frequently appeared in a single comment. This analysis was used to clarify the context of consumer conversations, particularly in identifying the connections among shade selection, purchase access, price, marketplace, and the types of products most frequently discussed.

Table 5. Keyword Co-occurrence Analysis

Keyword Pair	Frequency	Interpretation
blush – tint	51	Discussion of TAVI and decorative products was largely related to color and lip/cheek product combinations.
Lip – tint	35	Conversations about lip products were quite prominent and related to color results.
Buy – shade	34	Purchase activity often appeared together with the need to choose shades.
Buy – cushion	33	Complexion products became objects of transaction and purchase consideration.
Buy – tint	27	Tint products frequently appeared in the context of transactions and product searches.
Shade – tint	25	Color selection became an important issue for tint products.
Shopee – tint	24	Marketplace access became one of the purchase access contexts for tint products.
Price – tint	21	Discussions of tint were also related to price considerations.
Cushion – shade	19	Complexion products generated a need for shade information.

Source: Processed by the author, 2026.

Based on keyword co-occurrence analysis, the most frequently occurring word pairs show that consumer conversations were largely related to color selection, purchase access, and pre-purchase considerations. Pairs such as buy-shade, buy-cushion, shade-tint, Shopee-tint, price-tint, and cushion-shade show that transaction issues, shade selection, marketplaces, and price were interconnected in consumer conversations. This finding strengthens the pain point analysis results, showing that consumer comments about Paragon's masstige brands contained not only general opinions but also practical needs before purchasing, especially related to product availability, shade information, and price considerations.

CONCLUSION

This study analyzed consumer sentiment and pain points toward Paragon's masstige brands based on 488 Twitter/X comments on four brands, namely Instaperfect, Crystallure, Labore, and TAVI. Based on sentiment distribution, examples of neutral comments, pain point analysis, and keyword co-occurrence analysis, consumer conversations about Paragon's masstige brands were mostly at the information-seeking and purchase consideration stage. The dominance of neutral sentiment cannot be interpreted as low consumer interest, because many neutral comments actually contained product questions, buying and selling activities, review needs, price considerations, and information seeking regarding shade, product availability, and compatibility with consumer needs. Thus, neutral comments have important value because they can reflect consumers' information needs, uncertainty, and barriers before purchasing products.

From the classification perspective, Naive Bayes can provide an initial overview of sentiment distribution, but its performance remained limited because the model tended to follow the majority class, namely neutral sentiment. Sentiment analysis provides an overview of the polarity tendency of comments, while pain point analysis clarifies the specific issues that emerge behind these conversations. The main pain points identified were related to stock/access/transaction, shade/color, and price/promotion/value, indicating that consumers faced many barriers in product access, color selection, and price and product value considerations. These findings show that combining sentiment analysis and pain point analysis can help brands understand consumers' information needs, strengthen product education, and design digital communication that better aligns with consumers' pre-purchase considerations.

RECOMMENDATIONS

Based on the research results, brands need to strengthen digital communication that focuses on product education. Information that needs to be clarified includes shade selection guides, recommendations based on skin type, product reviews, product value, and product availability in purchase channels. Neutral comments also need attention because many contain consumer questions and uncertainties that can be directed toward purchase interest if addressed appropriately through educational content, interactive responses, and easily understood product information.

For future research, it is recommended that data sources should not only come from Twitter/X, but also be expanded to other platforms such as TikTok, Instagram, e-commerce, or beauty forums so that the overview of consumer conversations becomes more comprehensive. In addition, future research can use data balancing techniques or compare several other classification algorithms, such as Support Vector Machine, Random Forest, or deep learning-based methods, to improve the model's ability to recognize positive and negative classes. The development of pain point analysis methods can also be carried out using a more systematic approach so that the identification of consumer issues becomes more accurate and does not rely solely on keyword-based tagging.

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