

Method for Analysing Information on Psychosomatic Issues Based on Service Recipient Dissatisfaction

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Abstract

Recently, the proliferation of social networking services has facilitated free sharing of opinions and complaints by consumers. For companies, such reviews are a valuable source of information for product and service evaluation, and for identifying areas for improvement. In this investigation, the cosmetics industry was used as a case study for this phenomenon. Content related to 'skin' was extracted from consumer review information and related physical and mental problems were analysed. Specifically, a polarity dictionary specialized for cosmetics was built, and related reviews were extracted by identifying expressions of dissatisfaction related to the skin, such as 'itchiness', 'redness', and 'dryness'. By classifying and analysing problem types, this analysis revealed the trends in consumer dissatisfaction and related issues, discovering insights useful for improving services and products. Therefore, the present study identified the types and causes of problems in providing practical knowledge that contributes to enhanced consumer satisfaction, reduced product risk, and effective marketing strategies.

Keywords: social networking service, cosmetics, consumer dissatisfaction, text mining

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1. Introduction

Recently, with the spread of the internet and mobile devices, individuals are enabled to share daily events and impressions. Social networking services (SNS), such as X, Instagram, Facebook, YouTube, blogs, and review sites, function as platforms where consumers can instantly share their experiences with products and services. These online pieces of information contain simple product evaluations and reports of service satisfaction. In addition to information that is difficult to collect through conventional surveys and interviews, such as physical changes and psychological reactions after product use.

Among female consumers, purchasing behaviours are influenced by review information. For instance, for products with large individual differences in feel and effect, such as cosmetics, review information and

evaluations have a strong influence on purchasing behaviour [1, 2]. For companies, these reviews are crucial for understanding actual consumer perspective. Descriptions of physical and mental concerns that arise after a product or service is used cannot be overlooked from the perspective of quality control and risk management. For instance, there are cases where consumers who have used cosmetic products complain of physical discomfort, such as 'I got itchy', 'it turned red', or 'my skin became very dry', and cases where they express psychological distress, such as 'my pores are not covered', 'I feel like I have more spots', or 'I feel like I have aged'. This information is a crucial element that is directly related to product safety and reliability.

However, systematically extracting useful information from the vast amount of available data is challenging, and often depends on an individual analyst's interpretation.

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Furthermore, free descriptions on SNS posts and review sites have diverse expression methods and writing styles, and a mix of synonyms, similar expressions, and metaphorical expressions. Therefore, it is difficult to comprehensively and accurately extract descriptions related to physical and mental problems with conventional simple keyword searches and general sentiment analysis.

In this study, dissatisfaction reviews for cosmetic products were analysed and the tendencies of physical and mental problems experienced by consumers were elucidated to provide insights that will help companies deeply understand consumers' potential needs and dissatisfactions, and contribute to the development of safer, more reliable products and marketing strategies.

2. Research on Text and Emotion, Psychology, and Customer Reviews

2.1. Research Using Text Mining

Text mining is gaining increasing attention owing to the progress in the analysis of free descriptions in review information and various survey progress. Text mining is an analytical method for quantitatively handling large amounts of text [3, 4] and is utilized in analysing inquiries to call centres and review analysis. There are various definitions, and although the expressions differ slightly, they have the following commonalities [5]:

- Processing large volumes of documents and text
- Exploring and characterizing regularity, similarity, and patterns
- Discovering related information (relevance) and their chains
- Visualizing information, especially a large amount of text information
- Converting information into knowledge, and discovering and acquiring knowledge

Etchu et al. [6] analysed free descriptions in university class evaluation questionnaires, demonstrating the extremely difficult in objectively understanding and grasping the overall trend by reviewing over 3,000 free descriptions, and that even when summarized, there is a risk of the analysis becoming arbitrary or subjective. Consequently, they have attempted to analyse and summarize the text using text mining tools to automatically extract words, check frequently appearing words, and explore word co-occurrence relationships, thereby minimizing arbitrary risk.

Yui et al. [7] attempted to clarify how or whether users use different cosmetic review sites by comparing multiple sites using text mining tools, and if so, how they do so. In this prior study, a comparative analysis was conducted for three brands across their official online shops, LIPS, and @cosme. The results suggested that even for products of the same brand and category, differences were found in the range of user interests and concerns on each review site,

and that users may be selecting review sites according to their own interests and concerns.

2.2. Research on Sentiment and Emotional Reactions in Free Descriptions

Sensitivity analysis algorithms for extracting sensitivity information from various free descriptions have been studied for many years [8, 9], and their accuracy has gradually improved. Research that extracts opinions from comments written in the free description section of surveys or from data containing people's opinions is called reputation analysis or sentiment analysis [10, 11]. Kanayama and Nasukawa [12] defined expressions showing positive sentiment and negative sentiment extracted from comments as 'reputation expressions'. They stated that by extracting reputation expressions and classifying the extracted expressions, various useful pieces of information can be found. Additionally, Kobayashi et al. [13] and Higashiyama et al. [14] created Japanese evaluation polarity dictionaries, focusing on the polarity that indicates the sentiment of evaluation expressions.

Sentiment analysis is utilized in numerous studies worldwide. For example, Shah et al. [15] proposes a multi-task model that simultaneously classifies news topics and sentiment across a diverse dataset comprising 3,263 news records spanning eight categories: environment, health, education, technology, sports, business, lifestyle, and science. Furthermore, research on classification and accuracy is advancing. Kushwaha et al. [16] examines various sentiment analysis techniques, including traditional machine learning approaches and state-of-the-art deep learning models. The research explores language models based on pre-trained deep neural networks, demonstrating that they can analyse text sequences and classify sentiment as positive, negative, or neutral without requiring explicit human labelling.

2.3. Research on mental and physical stress and customer reviews

Research on psychological burden and stress reactions has mainly been conducted in the medical and psychology fields [17]. Attempts to extract psychological burden from free descriptions on SNS and review sites are increasing; however, it is difficult to accurately capture industry-specific expressions. In particular, the psychological reactions shown by cosmetics users include elements that are difficult to evaluate using general emotion categories, such as a decrease in self-esteem and anxiety due to changes in appearance and skin problems. Senoo et al. [18] state that one of the main effects of skincare products is a change in emotion, that is, 'it feels good to use'. The study revealed that while evaluations of physical properties, skin effects, and preferences are often conducted, evaluations of 'emotions', such as 'it feels good', are lacking. The study

analysed the emotional changes (pleasure to displeasure) when using three representative skincare products: facial cleanser, 'lotion', and 'emulsion'. Therefore, the emotional changes were exhibited using different behaviours in both quality and quantity for each item, thereby, suggesting the application of new evaluation methods during future product development.

Customer reviews of products are a key factor influencing purchasing behaviour, and research utilizing sentiment information is advancing. However, as mentioned earlier, text mining may depend on the interpretation of the individual analyst. Baskaran [19] proposes an integrated algorithm framework combining state-of-the-art sentiment analysis and machine learning (ML) algorithms to predict sales quality by automatically analysing online product reviews. Through a systematic process, they collected structured data from various sources, considering normalization, sentiment analysis, and feature selection paths to build an advanced predictive model, and achieved 88% accuracy in predicting sales quality. Sentiment analysis in cosmetics is characterized by significant individual variation. Therefore, grasping the overall positive/negative sentiment and its direction in questionnaire surveys is crucial. However, to clarify individual differences, interview results have to be analysed. Building a database that integrates these interview results with survey findings is essential for deepening analysis. However, because interview surveys contain personal information, protecting these data necessitates careful attention. Potential countermeasures include utilizing research such as the hierarchical adaptive evolution framework for privacy-preserving data disclosure [20, 21] and privacy-preserving encryption for big data analysis [22].

2.4. What will be done in this research?

Competition in the cosmetics industry is fierce, and improving consumer satisfaction and resolving complaints is one of the factors that enhances a company's competitive advantage. However, studies on review information analysis for physical discomfort or psychological distress are lacking. Many pieces of review information do not use direct evaluative words such as 'good' or 'bad', rather, evaluations are expressed through indirect, experiential descriptions such as 'my skin feels tight' or 'it stings', indicating the challenges in extracting and analysing these descriptions.

Therefore, this study focuses on the cosmetics industry and extracts expressions of dissatisfaction from consumer review information, specifically physical discomfort (e.g., itchiness, redness, and dryness) and psychological distress (e.g., anxiety, irritation, and disappointment). Then, based on the extracted information, physical and mental problem patterns were classified. KH Coder (<https://kncoder.net/>) is a text mining tool suitable for processing Japanese text and

can centrally execute various functions, such as extracting words through morphological analysis, measuring word frequency, and visualizing the co-occurrence relationships between words. The co-occurrence network is considered an effective means for visually and intuitively understanding consumer interests and dissatisfaction.

3. Research Data and Methods

3.1. Research Data and Dictionary Construction Methods

This study uses review information from the 'Discontent Survey Dataset' [23], provided by Insight Tech, Inc. (Former company name: Dissatisfaction Buying Centre, Inc.), and made available to researchers by the National Institute of Informatics. Approximately 5.25 million pieces of data from March 18, 2015, to March 12, 2017 (hereinafter referred to as 'dissatisfaction information') were analysed. Overall, the data has 222 categories, with dissatisfaction information in the cosmetics category, having 52,237 items.

In this study, a polarity dictionary was constructed specifically for cosmetics-related reviews, which were extracted based on dissatisfactory expressions related to the skin. The polarity dictionary was constructed by reviewing dissatisfaction information to extract terms related to skin problems. This included vocabulary expressing direct symptoms such as 'it hurts', 'it turns red', and 'it becomes itchy', onomatopoeic words used in various situations such as 'piripiri' (tingling) and 'hirihihi' (stinging). In addition to vocabulary expressing anxiety felt on the skin after use, such as 'aged' and 'I feel like I have more spots'. The dictionary was first constructed by extracting vocabulary from 300 sentences (Version 1). Then, expressions not included in Version 1 were added from another 300 sentences to fill in the gaps (Version 2). This process was repeated five times, creating a polarity dictionary from a total of 1,500 sentences. As a result, the dictionary included words such as 'vocabulary that expresses direct symptoms,' 'onomatopoeia used in various situations,' and 'vocabulary that expresses anxiety felt on the skin after use.' Ultimately, 289 words were registered. The specific contents are shown in Table 1. In addition, in Japanese, there are conjugated forms and particles, such as 'no' and 'ga'; therefore, the dictionary was supplemented with particles using '*' (such as 'hada * itai' (skin hurts) and 'hada * itakunaru' (skin becomes painful)), and registered as many conjugated forms as possible.

Overall, 13,159 reviews were extracted. In addition, the dissatisfaction information included answers to a question about consumers' future purchase intention for the products, with four options: 'stopped purchasing', 'decreased purchase frequency', 'no effect', and 'others'

(Table 2). Note that some of the texts sometimes contained positive expressions and dissatisfaction.

Table 1. Examples of vocabulary registered in the dictionary

Vocabulary describing direct symptoms	'pain', 'itching', 'redness', 'swelling', 'rough skin', 'dryness', 'stinging, hurt', etc.
Onomatopoeia used in various situations	'piripiri (tingling)', 'hirihiri (stinging)', 'potsupotsu (spots)', 'kasakasa (dry)', 'chikuchiku (prickling)', etc.
Vocabulary describing discomfort felt after use	'aging', '(skin) becoming dirty', 'spots (increasing)', 'worsening', etc.

Table 2. Number of extracted data items with descriptions related to 'skin' for each purchase intention

Stopped purchasing	Decreased purchase frequency	No effect	Others	Total
2,122	890	856	9,291	13,159

3.2. Research Methods

In this study, KH Coder was used to visualize the co-occurrence relationships between keywords extracted from skin-related dissatisfaction information. By drawing co-occurrence network diagrams, the frequency of extracted words and relationships among keywords can be analysed. After comparing the proportions of the three classifications in the developed sentiment dictionary, the dissatisfaction information was compared in the following combinations.

1. Comparison of the content of dissatisfaction information in the four responses: 'stopped

purchasing', 'decreased purchase frequency', 'no effect', and 'others'.

2. Comparison of frequently appearing words in the four responses: 'stopped purchasing', 'decreased purchase frequency', 'no effect', and 'others'.

The settings for the KH Coder co-occurrence network were as follows: the aggregation unit was 'sentence', and parts of speech were 'noun', 'noun B', 'noun C', 'adjective', 'adjective B', 'adjectival verb', 'unknown word', and 'tag' [24]. In KH Coder, the larger the circle is, the more frequently the word appears in the text. The darker the colour of the circle, the more central the term is to the overall network.

4. Analysis of Dissatisfaction Information

4.1. Analysis of Dissatisfaction Based on Purchase Motivation

This section conducted a comparative analysis of the dissatisfaction information content in the four responses: 'stopped purchasing', 'decreased purchase frequency', 'no effect' and 'others'.

Figure 1 displays the co-occurrence network of the dissatisfaction information from people whose answer was 'stopped purchasing'. In (A), direct symptoms, such as 'itchy', 'painful', and 'red', are linked to physical locations such as the 'face' and 'eyes', which are things that appeared on the body after use. In (B), the onomatopoeic word 'dry (kasakasa)' is linked to physical locations such as the 'hands' and 'lips'. Specific products, such as 'cream' and 'lip balm', are also linked to physical locations. Additionally, detailed analysis of the text revealed dissatisfaction with symptoms not being alleviated even after use, such as 'the dryness would not heal' or 'it became dry (skin)', and dissatisfaction with symptoms appearing after use linked to an onomatopoeia. Both (A) and (B) are states involving symptoms. In (C), 'ineffective (no effect)' is linked to symptoms that a person wants to fix, such as 'blemish' and 'pimple'. This reflects the dissatisfaction that, despite choosing the appropriate cosmetics for symptom alleviation, the expected effect was not achieved. In (D), 'feeling' and 'bad' are linked, and because they are linked to 'smell', 'scent', and 'odour', discomfort with the smell is expressed. Further, 'good' is linked to 'fragrance', suggesting a sense of satisfaction. In (E), 'expensive', 'price', and 'disappointing' are linked, showing that it is related to dissatisfaction with the high price.

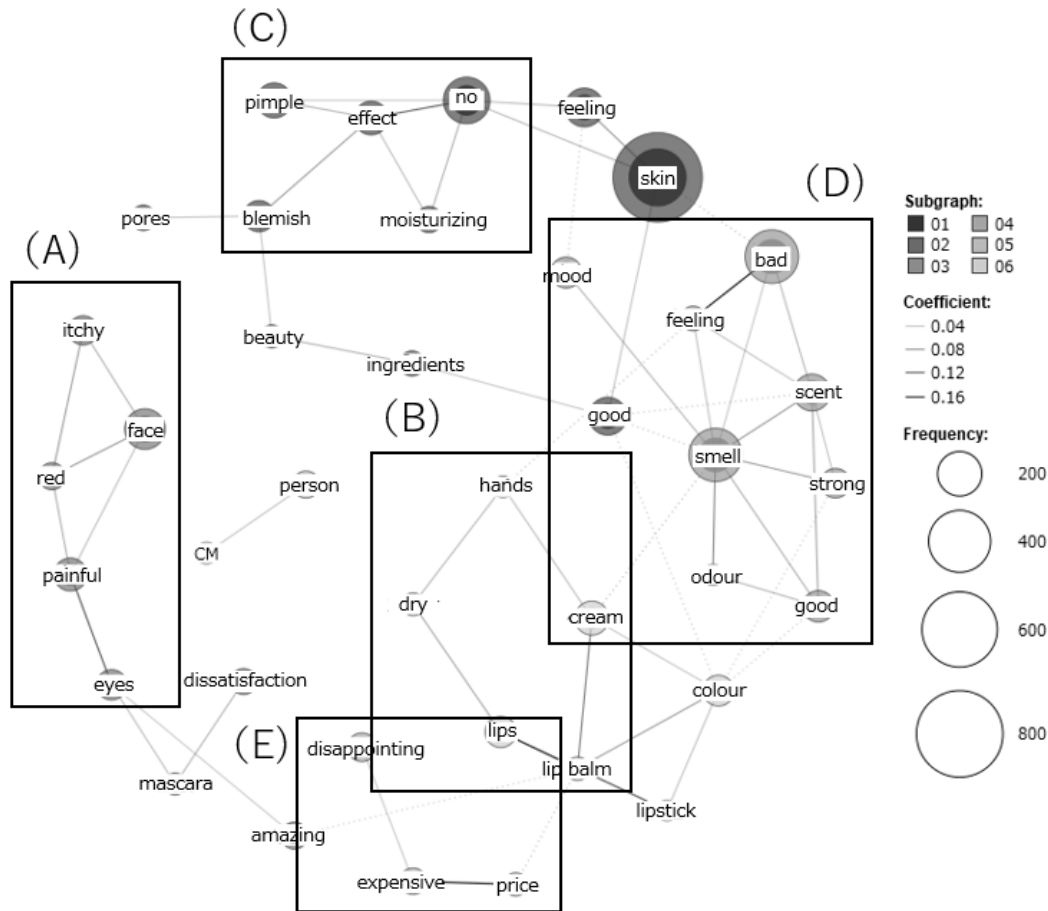


Figure 1. Co-occurrence network of people who answered ‘stopped purchasing’.

Figure 2 demonstrates the co-occurrence network of the dissatisfaction information from people who answered ‘decreased purchase frequency’. In (A), a physical location ‘eyes’ is linked to a symptom ‘painful’. In addition, specific products and services, such as ‘mascara’ and ‘cleansing’, are linked. This expresses pain from using mascara near the eyes, or pain when using cleansing products to remove mascara (there are also many descriptions of dissatisfaction with mascara being difficult to remove). In (B), the onomatopoeic word ‘dry (kasakasa)’ is linked to the physical location ‘lips’. It is also linked to specific products such as ‘lip balm’ and the season ‘winter’. A detailed analysis of the text revealed that ‘winter’ was a related term because dryness often occurs in winter; hence, using lip balm in winter is also linked. Regarding symptom alleviation, there was a dissatisfaction with the lack of symptom relief; however, there were also requests, such as ‘I want something like ***’. In (C), ‘smell’ and ‘strong’ are

linked, and dissatisfaction with the smell is present. This also has a slight connection to ‘cream’, and there was dissatisfaction with the cream’s smell. In (D), ‘ineffective (no effect)’ is linked to a physical location, ‘face’, and symptoms that a person wants to fix, such as ‘pimple’, ‘pores’, and ‘blemish’. This reflects the dissatisfaction that, despite choosing the appropriate cosmetics for symptom alleviation, the expected effect was not achieved. In (E), ‘skin’, ‘no’, ‘disappointing’, and ‘dissatisfaction’ are linked. A detailed analysis of the text suggests disappointment and dissatisfaction with the cosmetics not being suitable for them, such as ‘it is a shame because it does not suit my skin’. In (F), ‘price’, ‘expensive’, and ‘cheap’ are linked, indicating the existence of dissatisfaction with the ‘expensive’ price and satisfaction with the ‘cheap’ price, showing both positive and negative emotions.

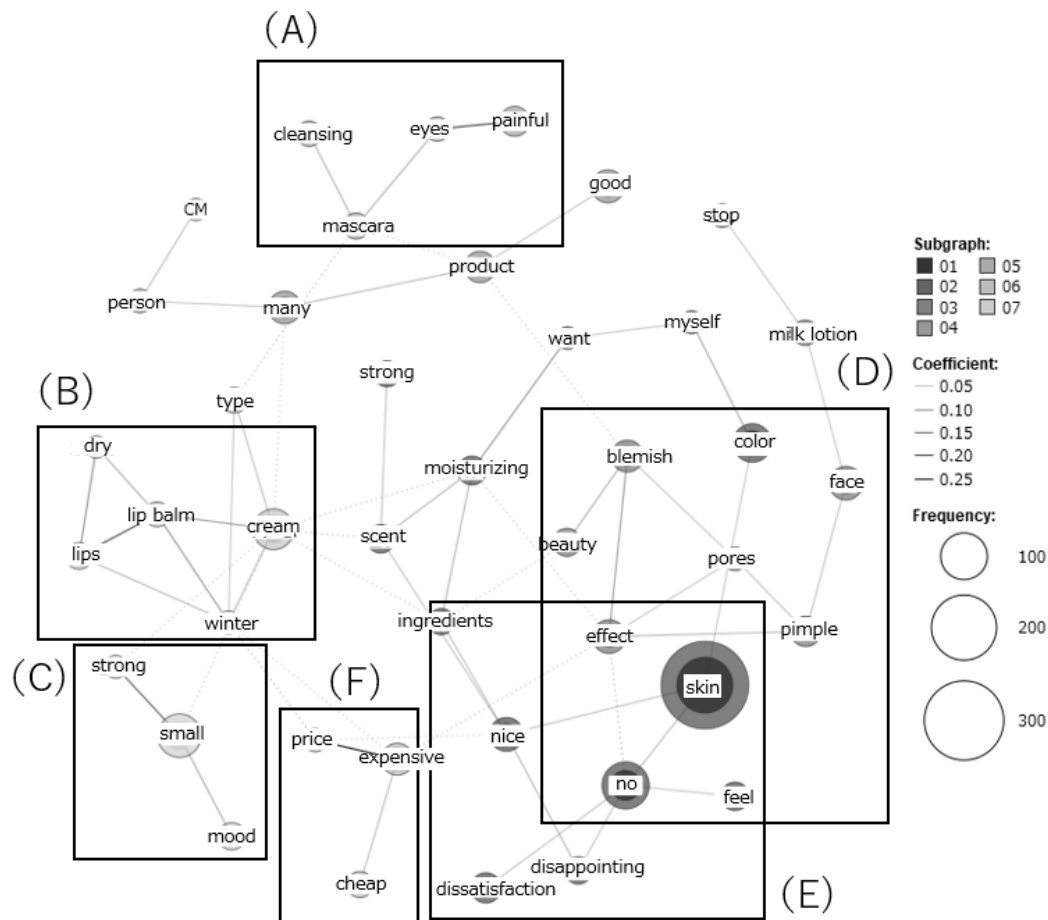


Figure 2. Co-occurrence network of people who answered 'decreased purchase frequency'.

Figure 3 shows the co-occurrence network of the dissatisfaction information from people whose answer was 'no effect'. In (A), a physical location 'eyes' is linked to a direct symptom 'painful', which appeared on the body after use. In (B), 'feeling' and 'bad' are linked, and a detailed analysis of the text revealed dissatisfaction with the feeling. In (C), 'skin', 'sensitive', and 'dissatisfaction' are linked, and a detailed analysis of the text revealed dissatisfaction with the lack of products available for people with sensitive skin types and the price. In (D), 'cream', 'lip balm', 'lips', 'lipstick', and 'want' are linked, and a detailed analysis of the text revealed a request for products that are more

effective for sensitive skin types or dryness. In (E), 'smell' and 'good' are linked, and a detailed analysis of the text revealed a request for a 'what good-smelling product to be released', but also negative content such as 'I feel that good-smelling products are not very effective'. In (F), 'foundation', 'colour', and 'want' are linked, which is a request. In (G), 'effect' and 'high' are linked, and there was positive content such as 'I am interested because the effect is high', a request such as 'I want something with a high impact', and negative content such as 'I cannot find something with a high impact'.

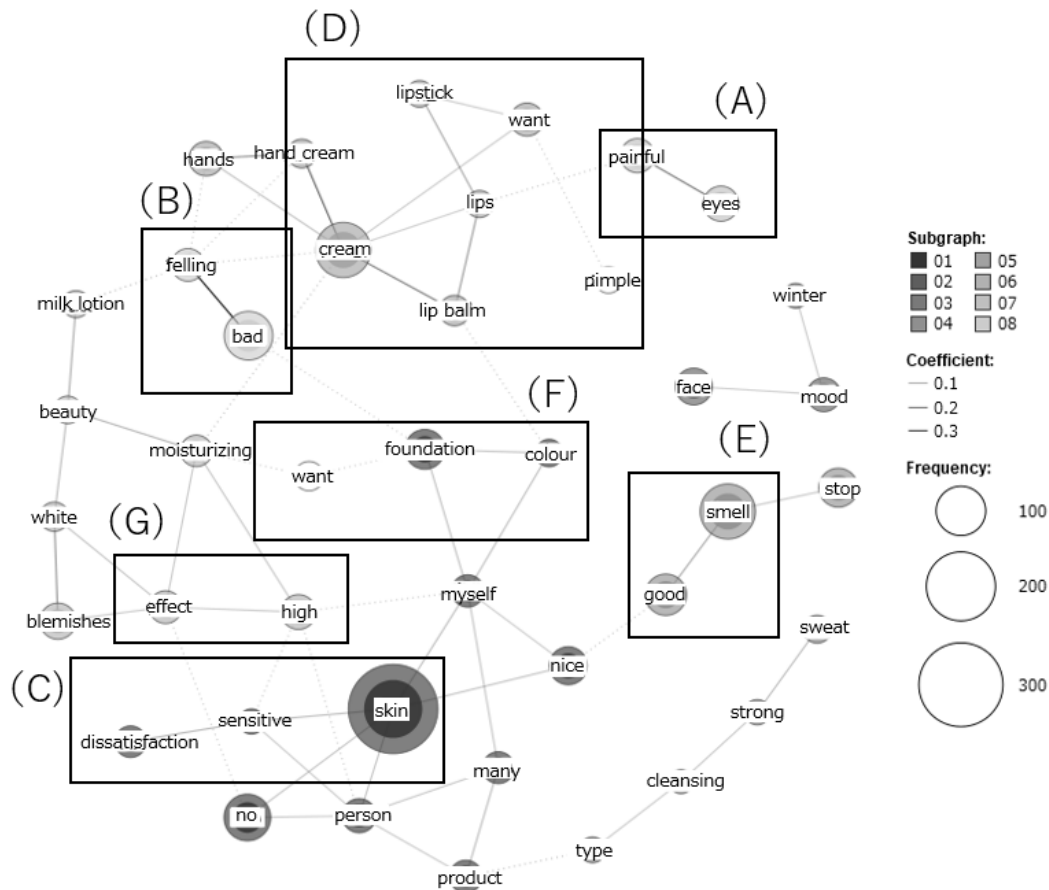


Figure 3. Co-occurrence network of people who answered 'no effect'.

Figure 4 presents the co-occurrence network of the dissatisfaction information from people whose answer was 'others'. In (A), direct symptoms such as 'itchy' and 'painful' are linked to physical locations such as 'face' and 'eyes', which are things that appeared on the body after use. In (B), the onomatopoeic word 'day (kasakasa)' is also linked to physical locations such as 'hands' and 'lips'. Specific products such as 'cream' and 'lip balm' are also linked, and a detailed analysis of the text revealed dissatisfaction with symptoms not being alleviated even after use, such as 'the dryness would not heal' or 'it actually got rougher'. Both (A) and (B) are states where symptoms have appeared. In (C), 'ineffective (no effect)' is linked to symptoms that a person wants to fix, such as 'pimple' and 'blemish'. This reflects the dissatisfaction that, despite

choosing the appropriate cosmetics for symptom alleviation, the expected effect was not achieved. In (D), 'feeling' and 'bad' are linked, due to discomfort with the feel, such as 'the slippery feeling is unpleasant' or 'it is sticky and undesirable'. In (E), 'smell', 'scent', and 'good' are linked, a positive expression that is also linked to 'strong', and there were also negative expressions, such as 'I am a little concerned that the smell or scent is too strong'. In (F), 'expensive' and 'cheap' are linked to price, indicating dissatisfaction with the 'expensive' price and satisfaction with the 'cheap' price, showing both positive and negative feelings. In (G), 'moisturizing', 'ingredients', and 'want' are linked, which is a request.

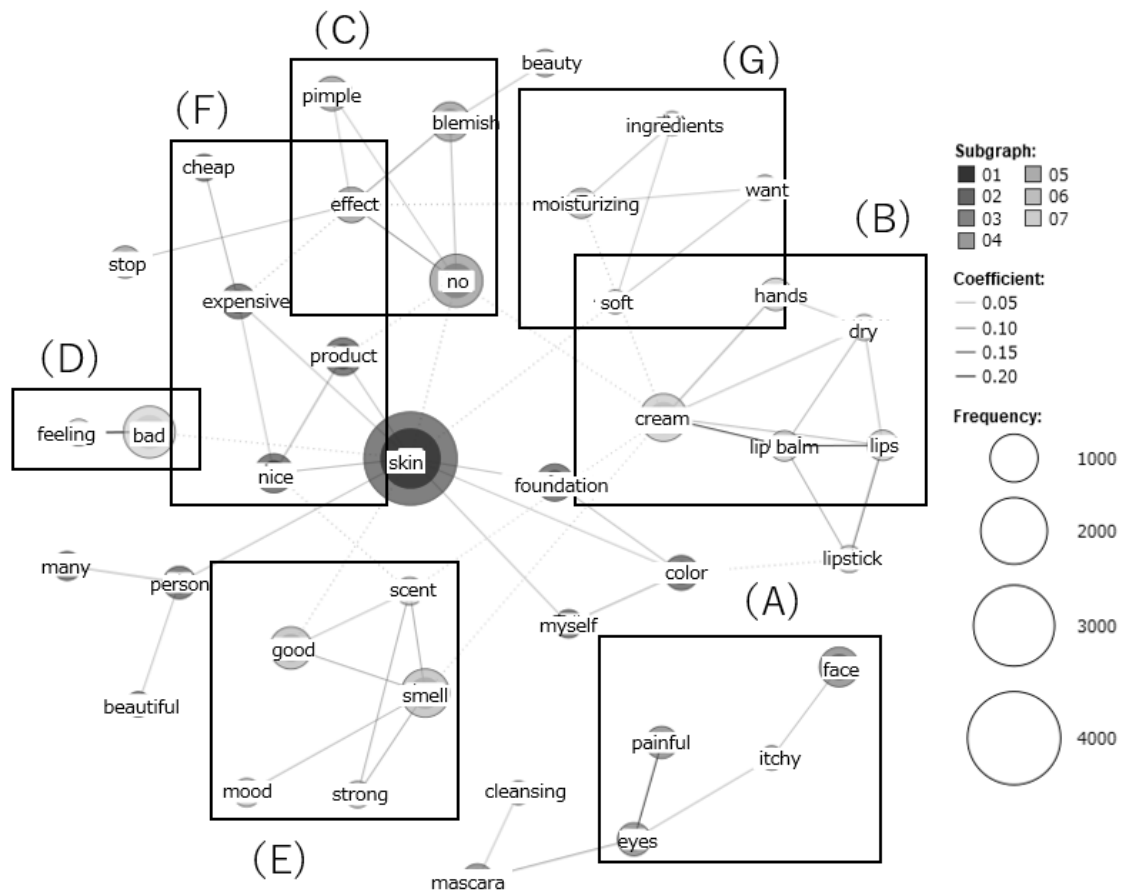


Figure 4. Co-occurrence network of people who answered 'others'.

4.2. Analysis of Trends in Physical and Mental Problems Based on Frequently Appearing Words

Trends of physical and mental problems were analysed by comparing the frequently appearing words in the KH Coder.

An analysis was performed by comparing the top 10 words in the frequently appearing adjective list for the four responses: 'stopped purchasing', 'decreased purchase frequency', 'no effect', and 'others'. The results are listed in Table 3.

Table 3. Top 10 most frequent words (adjectives)

	Stopped purchasing		Decreased purchase frequency		No effect		Others	
1	Bad	296	Bad	124	Bad	97	Bad	1187
2	Good	144	Good	51	Good	58	Good	655
3	Painful	107	Many	47	Expensive	48	Expensive	510
4	Strong	84	Expensive	45	Painful	46	Painful	434
5	Itchy	82	Painful	39	Many	40	Many	345
6	Red	69	Cheap	29	Want	33	Cheap	292
7	Expensive	66	Strong	29	Strong	24	Strong	285
8	Smelly	40	Few	22	Gentle	16	Want	276
9	Cheap	38	Want	21	Cheap	15	Itchy	235
10	Dirty	38	Gentle	18	Weak	15	Gentle	225

In particular, the three words ‘painful’, ‘itchy’, and ‘red’, which are linked to physical problems, are in the top 10 for ‘stopped purchasing’. For ‘decreased purchase frequency’ and ‘no effect’, only ‘painful’ is included, and for ‘others’, ‘painful’ and ‘itchy’ are included.

5. Discussion

In Figure 1, the review content of people who answered that they ‘stopped purchasing’ was analysed. Expressions such as ‘itchy’ and ‘painful’, representing direct symptoms, and ‘dry (kasakasa)’, an onomatopoeic word used in various situations, were linked to physical locations. These are specific and direct skin problems that consumers experience and require immediate action. Furthermore, because ‘unpleasant (feeling bad)’ was linked to ‘smell’, the fragrance during use, which is one aspect of the user experience, may be a factor in stopping a purchase. Words expressing anxiety felt on the skin after use, such as ‘ineffective (no effect)’, were also linked, and physical and mental problems were extracted in relation to specific symptoms including ‘blemish’ and ‘pimple’. In addition, there were mentions of price, with descriptions such as ‘expensive’ and ‘disappointing’. The reasons for stopping a purchase were often physical and mental problems, such as direct symptoms, discomfort after use, and a lack of efficacy. Moreover, there was dissatisfaction with the price, and as information requiring specific action from companies, the amount of information on how to improve is somewhat lacking.

In Figure 2, the review content of people who answered that their ‘purchase frequency decreased’ was analysed. Specific products such as ‘mascara’ and ‘cleansing’ were linked to direct locations and symptoms including ‘eyes’ and ‘painful’. While there were words expressing anxiety felt on the skin after use, such as ‘unpleasant (feeling bad)’, ‘smell’ was also linked to the positive expression ‘good’. Furthermore, there were specific seasons of dissatisfaction and requests for what they ‘want’, suggesting that consumers tend to describe what companies should specifically improve regarding physical and mental problems. Regarding price, as there were descriptions of both positive and negative feelings, price may not be a major issue if the points of dissatisfaction are improved.

In Figure 3, the review content of people who answered ‘no effect’ on their purchase intention was analysed. Like ‘stopped purchasing’ and ‘decreased purchase frequency’, there were expressions of direct locations and symptoms, as well as words expressing anxiety felt on the skin after use, such as ‘unpleasant (feeling bad)’. However, positive content, requests, and hopeful descriptions were also observed. A characteristic of this dataset is that, despite being a description of dissatisfaction, much positive content was included alongside the complaints. These can be organized as points for consumer satisfaction. For instance, there was a point about the lack of products for people with sensitive skin, which can be considered by

companies, suggesting the possibility of extracting content related to improvement and development.

In Figure 4, the review content of people who answered ‘others’ regarding their purchase intention was analysed. This response makes it impossible to predict what the consumer will do regarding future purchases. Although it contained information found in all other responses, such as content expressing direct locations and symptoms, anxiety felt on the skin after use, such as ‘unpleasant (feeling bad)’, and requests including ‘want’, it was a comprehensive overview. For instance, regarding price and scent, there was both positive and negative content; hence, classification is necessary. Similar to ‘stopped purchasing’, there is a slight lack of information.

In Table 3, frequently appearing adjectives in the four responses: ‘stopped purchasing’, ‘decreased purchase frequency’, ‘no effect’, and ‘others’ were compared. The words ‘painful’, ‘itchy’, and ‘red’ were common among the top 10 for those who answered, ‘stopped purchasing’, suggesting that direct symptoms and problems similar to these are the reason for stopping a purchase.

6. Conclusion

This study focused on consumer dissatisfaction information related to ‘skin’ in the Japanese cosmetics industry and extracted and analysed information about physical and mental concerns using co-occurrence network analysis. This enabled us to find differences in consumers’ expectations and dissatisfaction, as well as in the tendencies of dissatisfaction expressions, which can be utilized for marketing.

Direct symptoms and discomfort after use may be influencing consumer reasons related to ‘stopped purchasing’. However, for cases of ‘purchase frequency decreased’ or ‘no effect’, consumers described specific physical locations, symptoms that occurred, and symptoms they wanted fixed. Despite being dissatisfaction information, there were many positive words and relationships, as well as requests and expectations for products. This information is valuable for companies, as it can lead to improvements, developments, or the creation of new markets.

In the future, clarifying the characteristics of mental problems for specific products, such as ‘foundation’ and ‘lipstick’, and proposing a technique that enables early detection of the signs of these problems is necessary. Furthermore, because the word ‘want’ appeared frequently, fulfilling the specific requests of consumers is possible. Therefore, knowledge was collected for product development, product improvement, enhancing consumer satisfaction, and understanding consumer purchasing behaviour. Analysis incorporating interview data may also be effective, and we plan to implement it in the future.

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