Analysis of Dynamic Changes in Customer Sentiment on Product Features After the Outbreak of COVID-19 Based on Online Reviews

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Sudden changes in life and work patterns due to COVID-19 have affected customer requirements for the products. Under these circumstances, companies can achieve high profitability and customer satisfaction when they can efficiently identify and respond quickly to changing customer preferences caused by COVID-19. This article presents empirical research on dynamic changes in customer responses for product features caused by the spread of COVID-19 through sentiment analysis based on online reviews. A case study is conducted using new and refurbished smartphone reviews to investigate the dynamic changes in customer sentiment before/during COVID-19. The importance of the result is shown by comparing it to the actual market data.
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1 Introduction

The outbreak of COVID-19 has been a direct threat to human beings and led to a global crisis. Implementation of practices to prevent the spread of the virus has changed individuals' lives and societies [1,2]. These drastic life changes have also led to changes in the buying patterns of customers: surge in e-commerce, preference for trusted products (easy to return and use), reduced spending on non-essential goods, and shock to loyalty due to changes in the major drivers for consumers to choose brands [3–5].

These changes in customer buying patterns due to the emergence of COVID-19 have brought companies to face uncertainties and challenges. In this crisis, it is more important than ever to capture the customer requirements that have changed caused by COVID-19 and identify the key motivations for consumers to choose products. However, few studies have been done on dynamic changes in customer sentiment for product features following COVID-19 spread.

This article presents empirical research on dynamic changes in customer responses for product features caused by the spread of COVID-19 based on online reviews. Given that online purchases have increased during COVID-19 [6] and quick customer analysis and response in this crisis are needed, online review analysis during COVID-19 has the advantage of being able to detect dynamic changes in customers' preferences for a short period compared to traditional methods. The following research questions are addressed in this article:

(1) Will customers during COVID-19 have the same or similar sentiments as before COVID-19 toward the features of new and refurbished products?
(2) If the customers' sentiments for the feature had changed, how would the customers' sentiments for each feature of the new and refurbished product be different?

To answer these research questions, this study aims to find out important features of a specific product and analyze a significant change in positive/negative customer sentiment for features of new and refurbished products before and during COVID-19 based on customer online reviews. The methodologies used in each step in this study are based on previous relevant frameworks and studies focusing on feature extraction and customer sentiment analysis [7,8]. This study analyzes the customer's sentiment score and the adjectives that determine the sentiment score to identify whether customers have different sentiment before and during COVID-19. In addition, statistical verification was performed to determine the significance of the difference between the results before and during COVID-19.

2 Literature Review

Some studies investigated consumer changes due to COVID-19 through traditional methodologies, such as questionnaires and interviews. Bhargava and coworkers [9] surveyed whether consumer consumption declined after COVID-19 for each retail category. As a result, although spending on groceries and household supplies increased, other items (e.g., electronics) have decreased significantly. In addition, there are survey results showing that the pandemic has affected the demand for new products as well as refurbished products. Koshi [10] revealed that the sales for refurbished smartphones with low prices and affordability have increased due to the COVID-19. However, since these existing methodologies are time-consuming, it is not possible to collect the opinions of many people in a short time. Therefore, it is difficult to assume that these results are an overall customer opinion that can be used for immediate design/market strategy when market conditions change rapidly.

To address the problems of these methodologies, some researchers have proposed customer analysis methods for product design using online reviews. Some of them focused on extracting important product features from customer reviews. Product feature refers to the properties, sub-assembly, or parts of a product, and it is important to extract the appropriate characteristics of the product at the product design stage [11,12]. Online reviews provide designers with data to understand which attributes of their products are important to their customers. To identify product features based on online reviews, Suryadi and Kim [7] used word embedding and clustering. Words in online review sentences were embedded into vector space and then grouped into clusters by X-means clustering. Park and Kim [8] proposed a phrase embedding method for the feature extraction. They extracted phrases from the review data and embedded them using word vectors composing the phrase. Then, spectral clustering was applied to the embedded phrases. The method returned clusters consisting of sub-feature terms.

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Another research focused on customer sentiment analysis to find the customer's sentiment polarity for features of products based on online reviews. Park and Kwak [13] used online reviews to investigate the dynamic changes in customer needs for smartphones over time. In this study, feature-level sentiment analysis was performed for certain features of smartphones, and implications were derived through the analysis of referring rate, percentage of positive, and negative reviews. Bag et al. [14] developed a framework to build a prediction model based on the social perception score of the brand and review's polarity. Cameras were used for validation of the proposed model. However, there are few papers related to the dynamic changes in customers' sentiments about the features of products in connection with massive-scale disruption in the market, such as COVID-19. Considering the advantages of online review analysis, which allows obtaining information in a short time, online review analysis is expected to help product designers in crisis develop and improve their new product and customer marketing strategies.

3 Methodology and Application

This study aims to investigate the dynamic changes in customers' sentiments about the features of new and refurbished products in connection with COVID-19 based on online reviews. A case study is conducted using new and refurbished smartphone reviews to investigate the dynamic changes in customer sentiment before and during COVID-19. Figure 1 illustrates the workflow of the proposed methodology, which consists of two main processes: feature extraction and sentiment analysis. The details of each step are explained in the following sections through the case study.

3.1 Data Collection. In this study, two types of data are collected: (i) online customer reviews; (ii) product manual provided by manufacturers. Table 1 contains the details of the collected online review data collected through Amazon.com. Among the smartphones included in the Amazon 100 list as of Jul. 11, 2020, smartphones that were sold simultaneously during the analysis period (before- and during-) were targeted. The total number of reviews is 15,811 written from Oct. 20, 2019, to Jul. 11, 2020. Among them, the number of new smartphones and refurbished smartphones reviews is 5,856 and 9,955, respectively. The total number of analyzed smartphone models is 42, of which the number of new products is 25 and the number of refurbished products is 17. Also, the product manuals used in this study are manual documents distributed by manufacturers, all of which are provided online. The collected reviews are divided into four groups by two criteria: (i) product category and (ii) timing (before and during COVID-19). The first criterion was divided into "New" and "Renewed" products specified on Amazon. The second criterion is when COVID-19 started to affect this society. In this study, the baseline for COVID-19 was set to March based on the time when the closure started in most countries, including the US [15].

3.2 Smartphone Feature Extraction. For smartphone feature extraction, the methodology suggested by Park and Kim [8] was modified and used in this research. As shown in Fig. 1, feature extraction is composed of three main processes: preprocessing, phrase embedding, and phrase clustering.

3.2.1 Preprocessing Review Data. In this study, Spacy library in PYTHON was used for preprocessing the review data. The collected reviews have been organized by removing punctuation marks and changing uppercase letters to lowercase letters. Then, all words were lemmatized. Spacy nlp analyzes the sentences and returns parts of speech (POS)-tagging of each word and a dependency tree that represents the linguistic structure of a sentence. These results will be used in Sec. 3.3.

3.2.2 Phrase Embedding. In this section, feature-relevant phrases are embedded into vectors. First, words in review data were embedded into vectors. Gensim library in PYTHON was used for word embedding. The lemmatized words from the previous stage were used for input to word2vec modeling. The parameters were set as follows: the dimension of the vector is 100, the number of windows is 2, and the minimum word count is 8. After training, Gensim returned a set of word vectors. Park and Kim [8] filtered word vectors using POS-tagging to collect noun vectors only. However, this research skips the filtering process to extract more diverse feature-related phrases, such as "big screen" and "front camera."

Next, phrases in review data were extracted by using the Noun_chunk method and Textrank method of Spacy library in PYTHON. For the simplicity of the process, phrases consisting of two words were considered in this research. To obtain feature-related terms only, the phrases containing a word that are not mentioned in product manual documents were removed. The remaining phrases were embedded by Eq. (1) from Park and Kim [8], where $\mathbf{W_1}$ and $\mathbf{W_2}$ represent the vector of the first and second word in the phrase, respectively. The phrase vector is constructed by a weighted sum of these two word vectors. The weight for each word, a_i, is the ratio of frequencies in manual documents. To be specific, a_i is calculated by dividing the frequency of word i by the total frequency of two words.

$$Phrase\ vector = a_1\mathbf{W_1} + a_2\mathbf{W_2}$$
$$a_1 = \frac{F(W_1)}{F(W_1)+F(W_2)} \quad a_2 = \frac{F(W_2)}{F(W_1)+F(W_2)} \tag{1}$$

3.2.3 Phrase Clustering. To group similar phrases, spectral clustering was applied to the embedded phrases. The number of clusters was chosen by conducting multiple trials with $K = 48$ to 55.

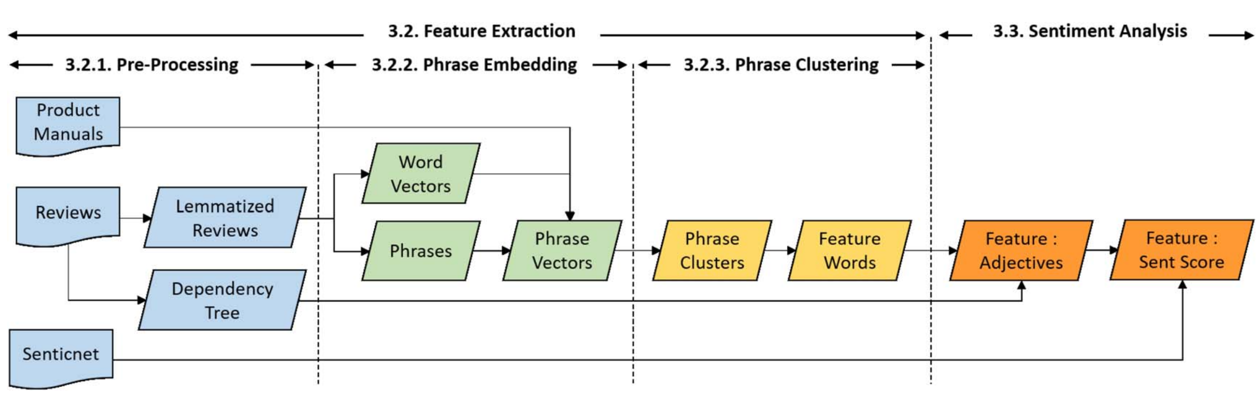

Fig. 1 The work flow of the methodology: feature extraction and sentiment analysis

Table 1 Details of the collected data

		Pre-COVID-19 (October 20, 2019–February 29, 2020)	During COVID-19 (March 1, 2020–July 11, 2020)
Number of reviews	New	3543	2313
	Refurbished	5005	4950
	Total	8548	7263

Table 2 Extracted feature phrases

Cluster label	Extracted phrases
Screen	Screen size, large screen, big screen, huge screen, small screen, screen resolution, screen technology, etc.
Memory	More storage, gb memory, enough space, internal memory, gb ram, more memory, extra storage, etc.
Camera	Front camera, selfie camera, rear camera, main camera, pixel camera, camera lens
Battery	Battery capacity, mah battery, huge battery, large battery, big battery, small battery, battery life, etc.
Security	Fingerprint reader, fingerprint sensor, fingerprint unlock, finger scanner, face recognition, iris scanner, etc.
Price	Price drop, great price, great value, decent price, affordable price, more money, bargain price, etc.

In this case study, $K = 54$ was chosen by manually analyzing the items in resulting clusters. Among 54 clusters, 8 feature-related clusters were selected, and they were summarized into six feature categories, as shown in Table 2. The first column shows the manual labeling based on the cluster members. The second column has the extracted phrases for each feature category. As mentioned in Sec. 3.2.2, this study extracts nonnoun phrases so that more diverse feature-related phrases can be obtained. Table 2 contains many nonnoun phrases such as "big screen," "internal memory," and "front camera."

3.3 Sentiment Analysis. This customer sentiment analysis is based on a previous relevant framework focusing on customer sentiment analysis by Suryadi and Kim [7]. In this study, target words are feature-related words, and they were obtained by decomposing feature-related phrases from the previous section.

First, each review sentence was scanned to check whether the sentence contains feature words. If it does, the sentence was further analyzed to find the adjectives connected to the feature word. The dependency tree from Sec. 3.2.1 was used in this task. All the adjectives directly or indirectly connected to the feature word were discovered. The analysis result created a set of feature word and sentiment pairs for every sentence. Next, based on these pairs, the reviewer's sentiment score for each feature was determined. All the adjectives in the pairs were quantified by Senticnet, a dictionary of sentiment scores. Senticnet returned the polarity (positive/negative) and the magnitude of the sentiment for the given adjective. Then, the mean value of all scores became the reviewer's sentiment for the target feature.

4 Result and Discussion

This section presents the results of customer sentiment analysis for new and refurbished products based on online reviews. Sections 4.1 and 4.2 show the analysis results for the customers' sentiment score and the adjectives that determine the customers' sentiment.

4.1 Comparison of Customer Sentiment Score Before and During COVID-19. In this study, the reviewers' sentiment score for each feature was calculated and analyzed. This analysis targets the reviews mentioned for each feature and scores the sentiments of the customers who wrote the reviews. The customer's sentiment score ranges from −1 to 1, where −1 is very negative, 0 is neutral, and 1 is very positive. The average sentiment score for each feature shows how customers feel about product features at each period, and whether there is a difference between the two periods. Figure 2 shows the difference in average customer sentiment scores before and during COVID-19 for new and refurbished products.

For new products, the results show that the customer sentiment score was lowered in all features during COVID-19, as shown in Fig. 2(*a*). A two-sample *t*-test to assess whether the average sentiment score reduction for each feature due to COVID-19 was significant. As a result, there were significant differences in the camera, battery, and price for new products. These results show that customer satisfaction with new products has decreased significantly for the camera, battery, and price during COVID-19.

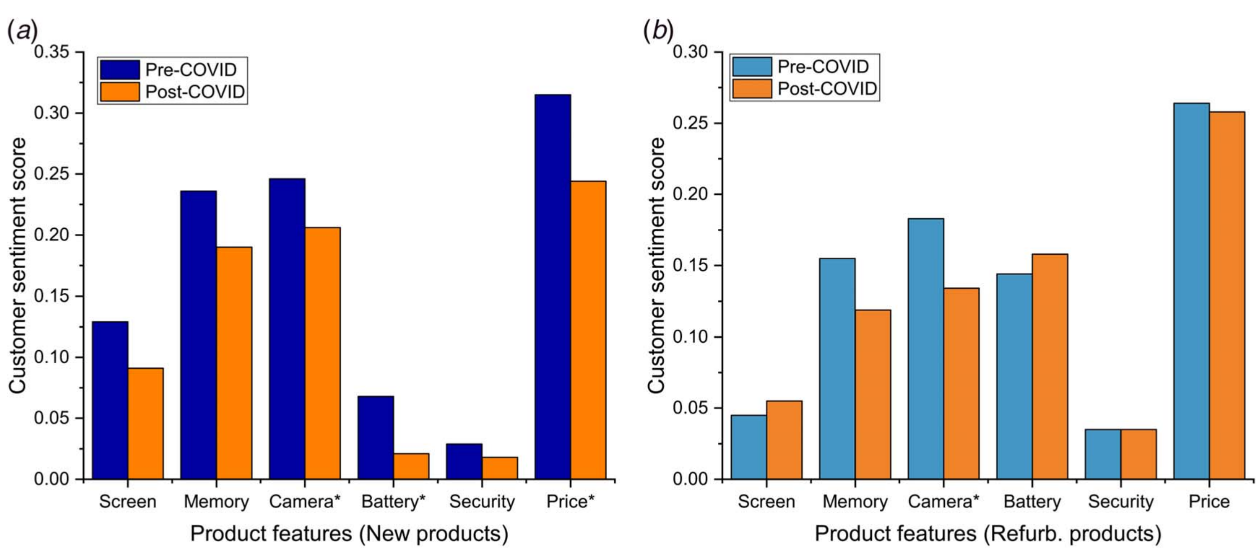

Fig. 2 The difference in customer sentiment score for (*a*) new products and (*b*) refurbished products. *The result is statistically significant at the $\alpha = 0.05$ level.

Figure 2(*b*) represents the difference in average customer sentiment scores before and during COVID-19 for refurbished products. In the case of refurbished products, the average sentiment score of the screen and battery increased while memory and camera decreased. The *t*-test shows that only the customer satisfaction with the camera was significantly reduced among the memory and camera.

4.2 Analysis of Adjectives That Determine Sentiments. According to previous analysis results (Sec. 4.1), there were significant changes in customer sentiment about specific features of the new and refurbished products before and during COVID-19. The results indicated that for new products, cameras, battery, and price factors negatively affect customer sentiment, whereas, for refurbished products, cameras negatively affect customer sentiment.

In this section, the top 20 adjectives used in each feature of the review were analyzed to see which factors contributed to this dissatisfaction. Among the top 20 adjectives used before and during COVID-19, adjectives used in two periods were classified as common adjectives, and adjectives that were not used in two periods were classified as unique adjectives. For common adjectives, the adjective usage ratio—frequency of use of adjectives divided by the number of features mentions in the review—was used to examine the change in the frequency of adjective use before and during COVID-19. The unique adjectives attempted to identify new issues that appeared after the outbreak of COVID-19 by categorizing adjectives newly appearing in the top 20 adjectives ranking after COVID-19.

4.2.1 New Products. For camera, the top 20 adjectives were largely classified as those related to overall evaluation, photography, and use. The adjective usage ratio in the overall evaluation confirmed that the use of adjectives, which represent most positive assessments, decreased during COVID-19 ("good," "amazing," "awesome," "wonderful"). In particular, during COVID-19, the use of adjectives related to photography, which is the detailed features of the camera, increased compared to before COVID-19 ("many," "nice," "front," "clear"). In the case of unique adjectives, additional issues with the rear camera and the sound from the camera when taking pictures were mentioned during COVID-19 ("rear" and "sound"). These results show that customers' positive overall evaluation of the camera during COVID-19 has decreased, and customers are more interested in the detailed functions of the front and/or rear camera than before COVID-19.

For the common adjective usage of the battery, it was confirmed that the percentage of positive adjectives used in the overall evaluation decreased compared to before COVID-19 ("good," "great," "amazing," "well"). For battery capacity, the use of positive adjectives decreased ("big," "huge") and the use of negative adjectives increased ("low"). For charging speed, the use of positive adjectives decreased ("fast," "full," "quick"). These results confirmed that the battery also decreased between positive adjectives for the overall evaluation and that customers' use of negative adjectives for battery capacity and charging speed increased.

For price, among the common adjectives, most adjectives that are positive for the price have declined overall since COVID-19 ("great," "good," "perfect," "worth," "amazing," "affordable," "reasonable," "nice," "incredible"). For unique adjectives, the use of negative adjectives appeared during COVID-19 ("bad," "less"). Compared to before COVID-19, the results indicated that the number of customers who positively rated the price of the same product has decreased.

Through the analysis of the set of adjectives that determine the sentiment score of each feature, it was possible to grasp the change in the customer's evaluation and attention level for the detailed features of the new product. For new products, customers during COVID-19 are more likely to pay attention to the detailed specifications of the front and rear cameras, sound problems during taking pictures, battery capacity and charging speed, and price burdens compared to those before COVID-19.

Interestingly, the results are consistent with the existing research results that customers began to search for good cameras that can take high-quality videos and pictures as social media activities, such as Instagram, Facebook live view, and TikTok have increased due to the restriction of gatherings during COVID-19 [16,17]. Also, the increase in smartphone usage has demanded large battery capacity and fast charging speed [18], and the economic downturn and increase in unemployment have made the price of smartphones burdensome for customers. For new smartphones, the results showed that it would be better to design a mid-tier product that focuses on the performance of camera and battery capacity rather than a high-priced product line.

4.2.2 Refurbished Products. For refurbished products, the top 20 adjectives used to mention the camera in customer reviews were extracted and analyzed. For the overall evaluation of the camera, some adjectives that are positive for the camera have declined since COVID-19 ("good," "great"). In addition, the percentage of customers who specifically mentioned the front and rear cameras was higher during COVID-19 ("rear," "front," "back"). For unique adjectives, the word "dead" appeared in the top 20 adjective list during COVID-19. According to these results, for refurbished products, customers during COVID-19 are more likely to pay attention to the detailed specs of the front and/or rear cameras compared to before COVID-19. In addition, quality checks will be required since camera malfunctions are mentioned in unique adjectives. According to our results, for refurbished smartphones, it would be better to release a model with high camera performance since they already have price competitiveness.

5 Conclusion

This article finds out crucial product features and analyzes customers' sentiments about various features of smartphones before and during COVID-19 by using customer online review data from Amazon. The collected online review data were analyzed by categorizing it into four groups by-product (new/refurbished smartphones) and period (before/during COVID-19). Based on the classified review data, this study analyzes the customers' sentiment score and the adjectives that determine the customers' sentiment to compare the differences between groups.

This analysis results showed the changes in customer sentiment following the spread of COVID-19 through online reviews. First, there are significant changes in customer sentiment about specific features of the new and refurbished products before and during COVID-19. The analysis of customer sentiment scores revealed that the camera, battery, and price factors negatively affect customer sentiment for new products, while the camera negatively affects customer sentiment for refurbished products. Also, the set of adjectives that determine the sentiment score of each feature was analyzed to identify the changes in customer evaluation and attention to specific features of products amid COVID-19 crisis.

The analysis results of this study have several meaningful implications amid COVID-19 crisis. The importance of these results can be demonstrated by showing a consistent practical example. In industry, discovering changes in customer preference is important in terms of a company's product strategy as well as individual product design. The result of this study suggested that COVID-19-affected customers' preferences for the battery and price in new smartphones. This finding can help companies set product strategies against unexpected changes due to the pandemic.

The result of this study can be validated by presenting the actual case in the smartphone market. Samsung releases its flagship smartphone (Galaxy S series) in the first quarter of every year. In 2020, the company released Galaxy S20 5G on March 6, 2020, with the release price starting from $999. However, Samsung had a significant drop in market share after COVID-19. In response to this unexpected event, the company changed its product strategy. For the first time, Samsung made a less-expensive variant of the Galaxy S model, Galaxy S20 FE. It lowered the price while maintaining most of the premium specifications, reflecting customer needs for cost-effectiveness. The product was released on October 2, 2020, with a release price of $699. In the US market, Samsung ended the year with a 5% growth in YoY sales volume [19]. This result shows that product strategy changes that reflect changes in customer preferences are effective.

Identifying customer changes in COVID-19 era and rapidly applying this information to new and refurbished product design development and/or improvement is a promising field of future research that must be explored to achieve more economic goals in a situation where everything is uncertain. The results of this study can be extended to future studies that build a model that predicts product demand in COVID-19 era (uncertain based situations) on online customer reviews. Research into product features that have attracted customers' attention for products that have seen a surge in demand after COVID-19 could also provide interesting design insights for product designers.

Conflict of Interest

There are no conflicts of interest.

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