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THE LIFE CYCLE OF ONLINE SMARTPHONE REVIEWS: INVESTIGATING DYNAMIC CHANGE IN CUSTOMER OPINION USING SENTIMENT ANALYSIS

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Abstract. *Sentiment analysis of online customer reviews is gaining increasing interests in the field of product design. This paper raises a concern for a common approach in the field of product design, where all reviews of a product are aggregated and analyzed as a whole. Considering that reviews are generated at different times over a long life cycle, a significant change in the review content is highly likely to exist between earlier and later reviews. To see if and how the review for the same product changes over time, this paper presents an empirical study investigating the life cycle of online smartphone reviews. Taking the Samsung Galaxy S5's 10,560 reviews posted in 2014-2018 as the subject, the dynamic change of customers' opinion was examined using lexicon-based, feature-level sentiment analysis. For three individual features (i.e., battery, display, and camera), the change in the referring rate as well as the percentages of positive and negative reviews are analyzed. The results show that, even if the product is the same, the customer evaluation can vary over time possibly due to product obsolescence over time and differences in the degree of consumers' innovativeness.*

Keywords: Sentiment analysis, Opinion mining, Review mining, Obsolescence, Analytics, Design intelligence, Consumer innovativeness

1. Introduction.

Sentiment analysis, also referred to as opinion mining, is a natural language processing (NLP) approach that extracts people's sentiments (opinion, attitude, subjectivity, emotion, etc.) from written text [1-3]. Recently, sentiment analysis of online customer reviews is receiving increasing interests in the field of product design, as online reviews have emerged as a promising source of information about consumer perception and preferences [4]. A great deal of research has been conducted with the aim of developing design methods based on sentiment analysis (e.g., [5-9]). Numerous empirical studies also have been reported, including studies for identifying important product features and their satisfaction levels (e.g., [10-12]), studies for categorizing customer requirements based on the KANO model (e.g., [13-16]), studies for comparing competitive advantages of different products (e.g., [3,17,18]), and so on.

In most existing studies, reviews for a product are aggregated and analyzed in an integrated manner despite the fact that each of the reviews is generated at different times. However, it is questionable if such aggregation is appropriate, especially in the case where reviews for a product are accumulated over a long time period. For example, it is not rare for cell phones that a new review is posted after several years from release (Figure 1). Considering differences in the degree of consumers' innovativeness and in the degree of product obsolescence over time, a significant change in the review content is highly likely to exist between earlier and later reviews [19,20]. Only a limited number

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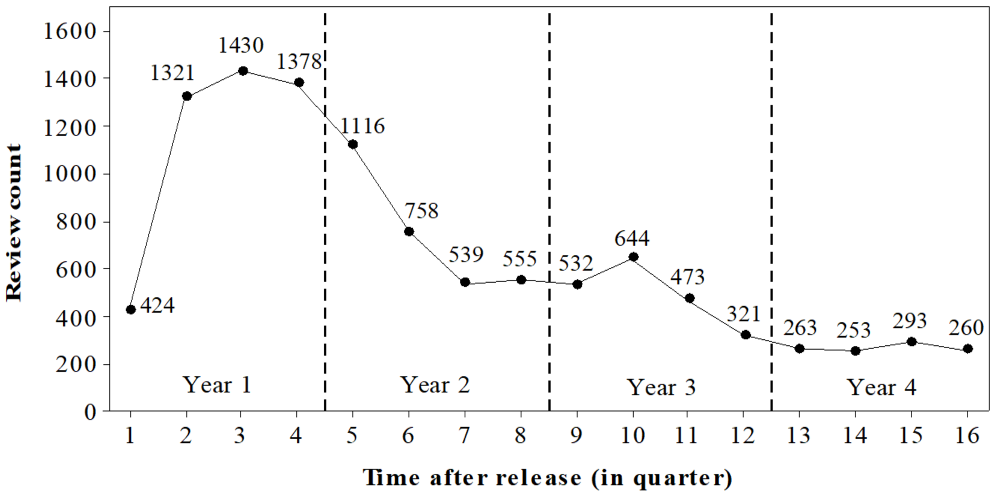


FIGURE 1. Number of product reviews for Galaxy S5 accumulated in Amazon every quarter

TABLE 1. Characteristics of review groups

Review group	Number of review	Percentage of review	Time of review (year and month)	Average word count	Average star rating
Year 1	4553	43.1%	2014.04 – 2015.03	55.21	4.33
Year 2	2968	28.1%	2015.04 – 2016.03	33.50	4.02
Year 3	1970	18.7%	2016.04 – 2017.03	37.83	3.68
Year 4	1069	10.1%	2017.04 – 2018.03	40.57	3.15

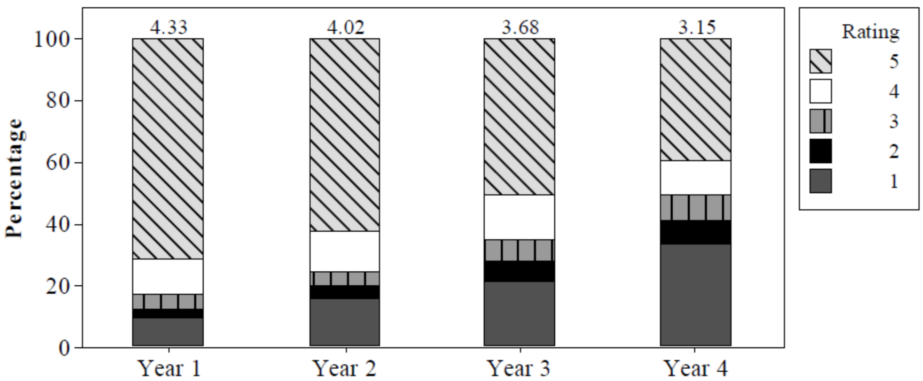


FIGURE 2. Change in the distribution of star ratings over time

of studies have incorporated time factor in the sentiment analysis (e.g., [16,21,22]), but studies for a single product at the feature level have been scarce.

To see if and how the review for the same product changes over time, this paper presents an empirical study investigating the life cycle of online smartphone reviews. Taking Samsung Galaxy S5 released in April 2014 as the target, its 10,560 reviews posted in Amazon.com for four years from April 2014 to March 2018 are collected and analyzed. Figure 1 shows the time-series data about the number of reviews accumulated in each quarter. In this paper, the reviews are divided into four groups (i.e., Year 1 – Year 4) according to the age of the product at the time of review (Table 1). As shown in Table 1 and Figure 2, the average star rating of the review groups gradually decreases over time, which implies possible changes in customer opinions for the product. To examine the dynamic change at the feature level, this paper conducts sentiment analysis focusing on three major smartphone features: battery, display, and camera. Following information is obtained for each feature and each review group:

- *Referring rate*: percentage of reviews referring the feature;
- *Positive rate*: percentage of reviews with positive opinion for the feature among the reviews referring the feature;
- *Negative rate*: percentage of reviews with negative opinion for the feature among the reviews referring the feature.

Comparing the results among the four review groups enables to address following three research questions.

- **Question 1**: How does the referring rate of a feature (i.e., the *feature importance*) change among the review groups?
- **Question 2**: How does customers' sentiment toward each feature change among review groups? Does positive rate (i.e., *satisfaction level*) decrease over time while negative rate (i.e., *dissatisfaction level*) increases?
- **Question 3**: Is there any difference among the features in the speed of sentiment change (i.e., the *speed of perceived obsolescence*)?

The rest of the paper is organized as follows. Section 2 briefly explains the methodology used in this paper. Section 3 presents the main analysis results. Finally, Section 4 concludes the paper with implications of the results and suggestions for future works.

2. **Methodology.** This study conducts lexicon-based (or, dictionary-based) sentiment analysis for three predefined smartphone features, i.e., battery, display, and camera. Python and the "SentimentR" package (https://CRAN.R-project.org/package=sen timentr) are used for the analysis. Figure 3 illustrates the overall process of the analysis. It mainly consists of five steps: data collection, lexicon creation, preprocessing, polarity detection, and information summarization.

1) **Data collection**: Online reviews for Galaxy S5 are collected from Amazon.com website, using a Java-based web crawler and open source library jsoup 1.10.2. The review data consists of five items: the smartphone manufacturer, date, star rating, review title, and text content.
2) **Lexicon creation**: The analysis requires lexicons for both sentiment words (i.e., positive and negative words) and smartphone features (i.e., synonyms of battery, display, and camera). As for the sentiment words, the lexicon built in SentimentR package (i.e., lexicon::hash_sentiment_jockers_rinker) is adopted as a basis, while making some modifications to the word list to make it more suitable for smartphone cases. For example, a sentence such as 'a few weeks after getting the phone the screen started glitching' is a negative sentence about the screen, but because the word 'glitching' is not included in the lexicon, sentence sensitivity is classified as neutral sentence. In this case, 'glitching' is added to the lexicon for improved accuracy. As for the smartphone feature, synonyms for battery, display, and camera are gathered from smartphone reviews. Reviews for Galaxy S Series are analyzed using Python's NLTK package (https://www.nltk.org/) to identify top 300 root words of the highest frequency. Synonyms for battery (e.g., batteri, charg, charger), display (e.g., screen, touch), and camera among the top 300 root words are added to the feature lexicon.
3) **Preprocessing**: Preprocessing is performed using Python to split original reviews into sentences. Only sentences containing the predefined features remain and proceed further.
4) **Polarity detection**: Using the SentimentR package, each sentence is classified into either positive or negative. The strength of the emotion is not counted. In case where

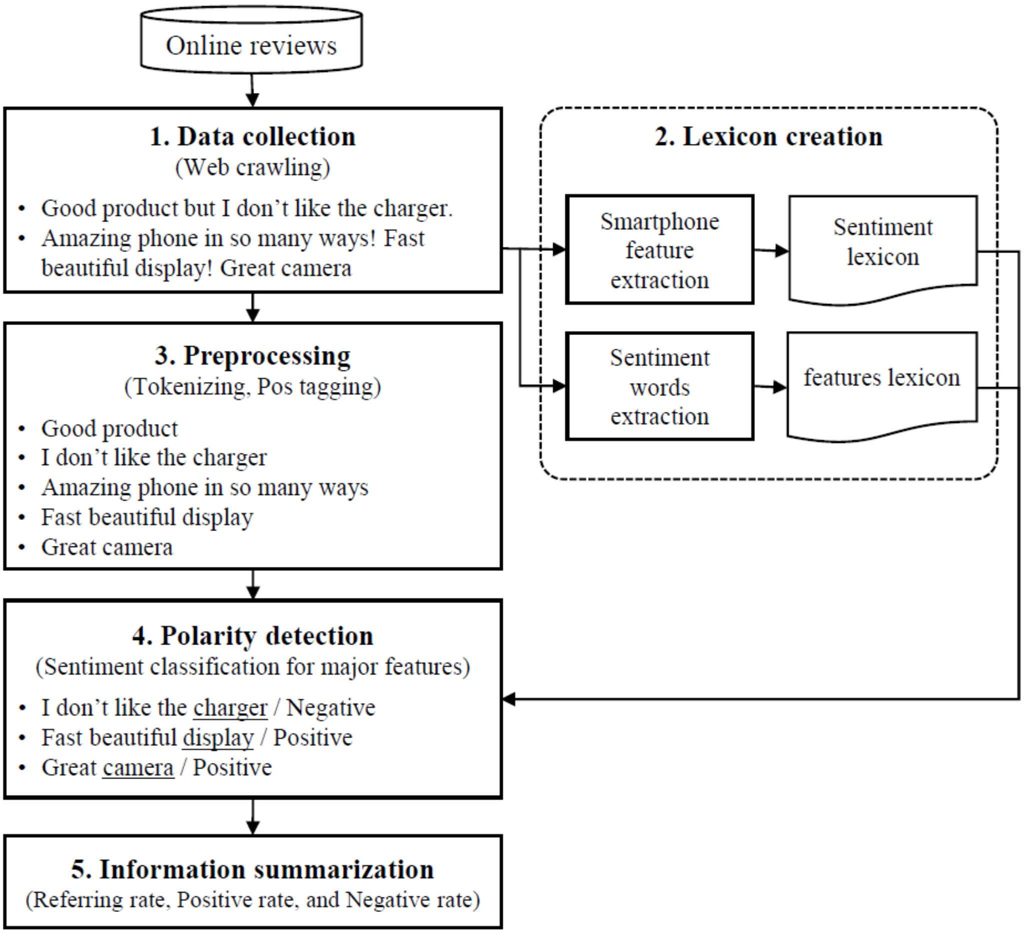


FIGURE 3. Overview of the sentiment analysis methodology

the sentence does not include any positive or negative word, it is noted as "neutral" and excluded from the analysis.

5) **Information summarization**: The result by sentence is combined at the review level to identify whether or not the review refers each of the three smartphone features once or more, and what opinions the review shows to the referred features. In this paper, the number of times of referring a feature is not distinguished. Similarly, the number of times of expressing opinions for a feature is not differentiated. For instance, there can be a review that includes two positive sentences about display. The current analysis concludes that "the review refers the display" and "the review is positive for the display". If a review includes both positive and negative sentences for the same feature, both polarities are accounted. Finally, the result by review is summarized at the review-group level into three values: referring rate, positive rate, and negative rate.

To test the accuracy of the analysis, 100 sentences were randomly selected from smartphone reviews and analyzed. The accuracy results in 84% for battery, 86% for display, and 92% for camera.

3. **Main Results.** Table 2 presents the main results of the analysis. It shows how the referring rate, positive rate, and negative rate of a feature change among the review groups.

Figure 4 illustrates how the referring rate of a feature (i.e., the importance of a feature) changes among the review groups, which indicates the change in the feature importance. Over the entire review life cycle, the ranking of feature remains the same; the battery is the most referred (in other words, the most important) feature, while the display and

TABLE 2. Analysis results (%)*

Review group	Battery			Display			Camera		
	Refer	Positive	Negative	Refer	Positive	Negative	Refer	Positive	Negative
Year 1	14.4	62.3	39.6	12.7	64.2	33.2	8.5	73.5	21.4
Year 2	13.5	48.6	42.4	8.4	44.8	39.5	5.8	58.5	39.2
Year 3	18.8	37.3	59.5	11.6	33.8	57.0	5.6	46.8	39.6
Year 4	22.5	36.5	65.1	15.1	21.1	58.4	3.9	61.9	40.5

*Refer: Referring rate (%); Positive: Positive rate (%); Negative: Negative rate (%)

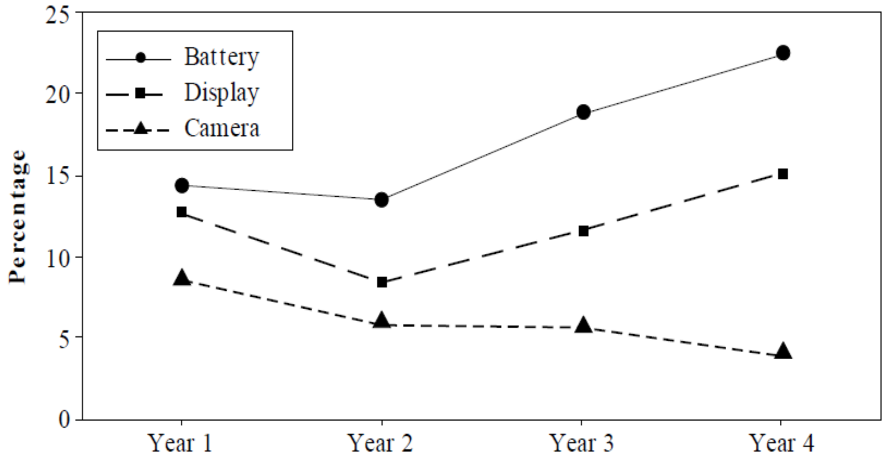


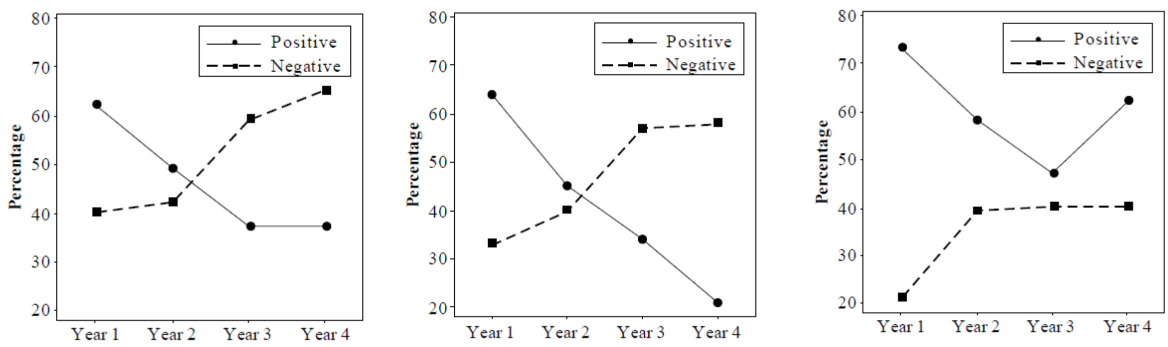
FIGURE 4. Percentage of reviews referring each smartphone feature

camera are the second and the last ones, respectively. However, the trend of the referring rate differs by feature. Whereas the battery and display show overall increasing trends, the camera shows a decreasing trend. This can be interpreted as that the later buyers (Year 3 and Year 4) care about the battery and display more than the earlier buyers (Year 1 and Year 2) do, while having less interests in the camera.

Implication 3.1. *Although the importance ranking of the smartphone features does not change, the degree of importance varies over time differently by feature. Battery and display show an increasing trend while camera shows a decreasing trend.*

Figure 5 describes how customers' sentiment toward each feature changes among review groups. Since more advanced versions of the product are newly introduced to the market every year, it is very likely that the satisfaction level for a feature gradually decreases over time. The results of the battery and display support such a supposition. In both cases, the positive rate monotonically decreases while the negative rate monotonically increases. A slight difference is observed only in the later phases between Year 3 and Year 4. In case of the battery, the positive rate stays almost the same while the negative rate increases. In case of the display, the opposite is true. The positive rate rapidly drops while the negative rate is almost the same. This can be interpreted as that the later customers are pickier about the battery than the display. Unlike the battery and display, the camera serves as an exception to the supposition. The positive rate for the camera decreases for the first three years, but it rather increases between Year 3 and Year 4. This means that the late buyers of Year 4 are satisfied with the camera in spite of its old specifications. They not only care less about the camera (Figure 4) but also have a lower standard for it compared to the earlier buyers.

Implication 3.2. *Customers' sentiment toward a feature changes over time, but the changing patterns vary by feature. In general, the satisfaction level for a feature tends to*



(a) Battery (b) Display (c) Camera

FIGURE 5. Sentiment for smartphone features

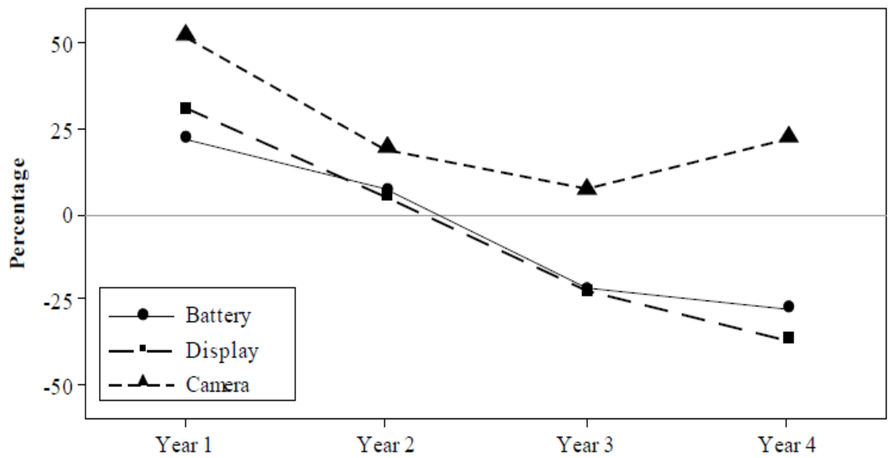


FIGURE 6. Gap between positive and negative rates

decrease, whereas the dissatisfaction level tends to increase. However, exceptions can exist for some features, especially in the later phases of the life cycle representing late buyers with a low innovativeness.

Figure 6 shows how the gap between the positive and the negative rates changes among the review groups. At first, the positive opinion outweighs the negative one for every feature. After two years, negative opinion gets stronger for the battery and display and the gap value becomes negative. Such a decrease in the gap can be regarded as perceived obsolescence of the feature, and the inclination of each feature line can be an indicator of the obsolescence speed. The figure implies that the speed of perceived obsolescence differs by feature and time. Overall, the battery and display experience greater obsolescence than the camera. However, the camera shows the fastest obsolescence in earlier phase between Year 1 and Year 2. The battery and display experience the fastest obsolescence between Year 2 and 3. Between the battery and display, the display shows faster obsolescence in the earlier phase than the battery, and the opposite is true in the later phase.

Implication 3.3. *The speed of perceived obsolescence and the changing pattern differ not only by feature but also by time.*

4. **Conclusion.** In this paper, the dynamic change of customers' opinion for the same product was analyzed using feature-level sentiment analysis. The results show that, even if the product is the same, the customer evaluation can vary over time possibly due to product obsolescence and customers' degree of innovativeness. The results raise a concern for the common approaches in the field of product design, where all reviews of a product

are aggregated and analyzed as a whole. When the reviews are posted and written by whom should be incorporated to improve the quality of the analysis.

The results also provide clues to the requirement differences between early buyers and late buyers. As environmental issues become increasingly important, extending product longevity via reuse, remanufacturing, sharing, etc., is emerging as a promising strategy. For such a strategy, it is essential to track the change in customer requirements. To the authors' best knowledge, this paper is one of the first attempts in this context that apply the feature-level sentiment analysis to the time-series data of a single product.

Since a single product model is analyzed in the paper, it is hard to generalize the results. In the future, the analysis will be extended to different smartphone models and to various product categories. Improving the accuracy of the analysis method is another future work.

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