Abstract

As a large number of online reviews are loaded on e-commerce platforms in recent days, companies are being able to measure customer satisfaction reflecting VoC (Voice of Customer) with big data analytics. This paper proposes the improved framework for identifying characteristics of customer satisfaction dimensions (CSD) based on Kano model using BERT (Bidirectional Encoder Representations from Transformers), GBM (Gradient Boosting Machine), and SHAP (Shapley Additive eXplanation). We proved each model outperformance by comparing other models which previous studies have used. And this paper suggests the unified rule of Kano model classification using SHAP. Furthermore, we conducted empirical studies regarding smartphone and smartwatch products which suggest the direction of product enhancement/development strategy and multi-product level customer segmentation strategy to product manufacturers. This shows proposed methodology's effectiveness and usefulness on industrial analysis.

Keywords : Customer Satisfaction, Smartphone, Smartwatch, BERT (Bidirectional Encoder Representations from Transformers), Kano model, SHAP (SHapley Additive eXplanation)

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1. Introduction

Understanding Customer Satisfaction is important for companies to develop or improve product or service which derives brand loyalty (Chiang, Guo, and Pai, 2008; Hallowell, 1996; Hui, Wan, and Ho 2007; Kim, Ng, and Kim 2009; Sepehr and Head, 2008). This study defines customer satisfaction as a customer' subjective evaluation of a product or service from customer requirement, expectation and its actual performance (Anderson, Fornell, and Lehmann 1994; Oliver 1980; Woodruff, Cadotte, and Jenkins 1983). It is constructed based on multidimensional characteristics of product in which we call them as customer satisfaction dimension (CSD). As each of CSD is measured accurately, a firm can concentrate on customers' requirement and expectation in a limited resource and may provide high customer value to customers (Goswami, Daultani, and Tiwari, 2017; Huang et al., 2018; Liu et al., 2018; Wang and Wang 2018).

As customer's online shopping related behaviors are permanent in recent days, numerous customer data are accumulated in online shopping platforms. In online platforms, customer generated data are highly valuable in understanding customer's concern, expectation, and sentiments since the company can reflect VoC (voice of customer) in business. One of customer generated data is online review which only the customers who purchased product have a right to write. Online review has competitive advantages relative to survey data in various aspects. Compared to survey data, online reviews can be easily collected with large amount and low cost. Moreover, companies can listen customer's opinion with open answer which contains much various and naive topics while survey respondents are required to answer their opinion in a closed form.

With infinite opportunities to utilize online reviews in analyzing product or service, recent studies started to propose big data methods to measure or model customer satisfaction. The majority of studies identified customer satisfaction dimensions (CSDs) based on NLP (Natural Language Processing) techniques (Guo, Barnes, and Jia, 2017; Tirunillai and Tellis, 2014). Kano model, introduced by Kano, Seraku, Takahashi, and Tsuji (1984), is a two-dimensional model which classifies product attributes into several categories (i.e. Must-be, Performance, Excitement, Reverse, Indifferent CSD). CSDs with different Kano category have different effect on customer satisfaction. For example, let's assume one CSD is must-be. Then even if this CSD fulfills customers, it doesn't influence on customer satisfaction positively but have a negative effect on customer satisfaction if it is not fulfilled. However, as for excitement CSD, this doesn't negatively give an effect on customer satisfaction even though it fails to fulfill customer requirement or expectation while it helps customer satisfaction to be increased when it is fulfilled. As firms can identify each CSDs feature in terms of customer requirement, expectation, and satisfaction, identifying each CSDs' Kano category is highly valuable in product or service enhancement.

Ordinarily, existing studies collected customer responses by survey method. However, survey method in Kano model has a limitation in that researchers need to arbitrarily determine a type of CSDs before surveys are sent to customers. These days, many studies used NLP techniques to extract CSDs with the researcher's least subjective engagement (Hou et al., 2019; Ou, Huynh, and Sriboonchitta, 2018). Jin, Jia, and Chen (2021) applied Kansei-integrated Kano model in the aspect of product design by using online reviews. And Kim and Yoo (2020) tried to clarify the delighter in Kano model with big data analysis. Xiao, Wei, and Dong (2016) proposed effect-based Kano model. In effect-based Kano model, Kano category is determined by the effect of customer's opinions, sentiments, attitudes on customer satisfaction. Bi et al (2019) also applied effect-based Kano model on identifying CSD characteristics. According to Bi et al (2019), SVM (Support Vector Machine) which is unsupervised learning was adopted in identifying customer sentiment on each CSDs and ENNM (Ensemble Neural

Network based Model) was proposed in measuring the effect of customer sentiments toward CSDs on customer satisfaction. However, most of existing studies didn't validate their model performance with accuracy, loss related measures. Since high model performance implies the model executes its work well (i.e. Customer sentiment classification, Prediction of the effect of sentiments toward CSDs on customer satisfaction), the model performance needs to be verified.

Moreover, previous studies established the criteria of classifying Kano categories based on their proposed model which explains the effect of CSD fulfillment on customer satisfaction. But most of criteria are only proposed model specific that can't be adjusted in other models. Thus, the consistent method which can be applied in all kinds of models is necessary to compare with CSD fulfillment effect in various studies.

The number of smartphone sales over 1.5 billion marked the peak in 2018 and has been keep declined until 2020. It might be that the most of potential customers become smartphone user since 2007. However, we suppose that smartphone related technologies are already highly developed so that it's hard for smartphone manufacturers to suggest new innovative customer value to potential and existing smartphone users. As customers get used to smartphones, their requirement and expectation toward smartphone is on high level. In the perspective of Kano model, Kano category can be distinguished by customer requirement and expectation (Hartono and Chuan, 2011; Madzik, 2018; Pai et al., 2018). As the level of requirement and expectation is raised, kano category changes from excitement CSD to performance CSD or from performance CSD to must-be CSD. Bi et al (2019) identified Kano category of smartphone released from 2012 to 2016. Bi et al (2019) extracted 18 smartphone CSDs which are composed of 6 Excitement CSDs, 5 Performance CSDs, and 7 Must-be CSDs. But there was no further study that clarifies CSDs of smartphone released after 2016.

Since smartphone industry has been become mature, manufacturers segmented customer group normally into low, standard, premium group. Low product can lower price hurdle to potential customers with providing relatively low quality meanwhile premium product targets on high-tech oriented customers who have intention to pay premium price of a product. But it has not verified that each product line users are actually what manufacturers targeted on.

Since mid of 2010's, wearable products such as smartwatch and wireless earphone have been introduced and innovated traditional market. Especially, smartwatch market industry has been being dramatically growing in recent years. As these products are highly dependent on smartphone, not only existing smartwatch customers but also smartphone users who are regarded as potential smartwatch user should be considered from product development phase. However, there is no previous study which tries to simultaneously conduct segmentation with two kinds of users.

To overcome the existing studies' limitations, the objectives of this study can be summarized as

Methodological perspective,

(1) To model the effects of customer sentiments (positive or negative) towards each CSD on customer satisfaction with state-of-art models.
(2) To propose the consistent method of Kano category classification

Business perspective,

(3) To clarify and compare CSDs by smartphone product line
(4) To classify customer segment in products integrative view by comparing CSDs of products

2. A framework for modeling customer satisfaction from online reviews

In this section, we explain a framework for measuring the effect of CSDs and modeling customer satisfaction. To facilitate understanding of section 3, the basic concepts of techniques used in each part are briefly illustrated as below.

(1) Customer Satisfaction

Customer satisfaction is a customer's subjective evaluation of a product or service from customer requirement, expectation and its actual performance (Anderson, Fornell, and Lehmann 1994; Oliver 1980; Woodruff, Cadotte, and Jenkins 1983). In this study, we regard customer satisfaction as a customer rating on product they purchased and used as like previous studies (Bi et al., 2019; Decker and Trusov 2010; Farhadloo, Patterson, and Rolland 2016; Guo, Barnes, and Jia 2017; Tirunillai and Tellis ,2014).

(2) Customer Satisfaction Dimension (CSD)

Customers usually evaluate their satisfaction toward a product based on their perceptions and interests of product related attributes. And similar with previous studies, CSD is identified by the cluster of words that describe an attribute of product or service (Bi et al., 2109; Guo, Barnes, and Jia 2017; Tirunillai and Tellis ,2014).

(3) SHAP

SHAP is a statistical model explanation methodology that measures each feature importance value for a particular prediction (Lundberg, 2017). It is founded on an additive feature importance measure with desirable properties of consistency, local accuracy, and missingness.

(4) Kano Category

The category of CSD is classified into five different Kano categories (i.e. performance CSD, must-be CSD, excitement CSD, reverse CSD and indifferent CSD). Each five categories are minutely elaborated as follows.

(i) Performance CSD: Performance CSD is positively related to customer satisfaction, which means customer satisfaction is increased when it is fulfilled meanwhile decreased when it is not fulfilled.

(ii) Must-be CSD: Must-be CSD doesn't help customer satisfaction to be increased even though it fulfilled customer's requirement and expectation. As the level of customer's requirement and expectation on CSD is high, it doesn't positively influence on customer satisfaction while negatively influence on customer satisfaction if it does not live up to customer expectation.

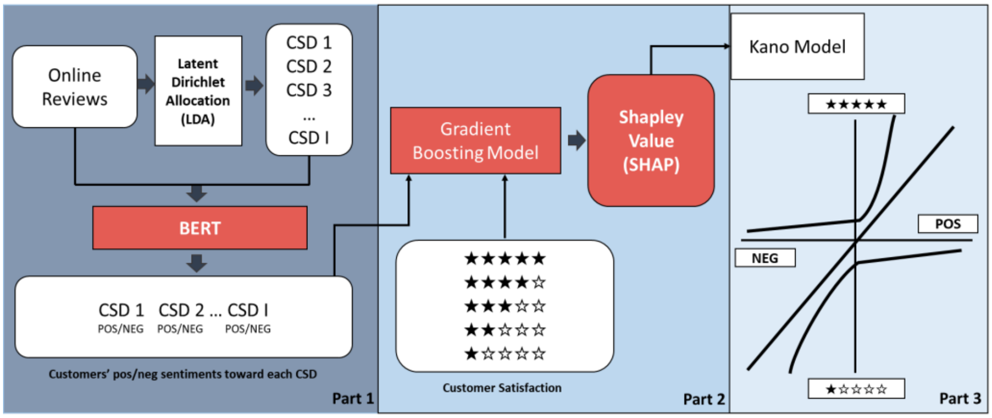
(iii) Excitement CSD: Excitement CSD is regarded as the opposite of must-be CSD. Since customer's requirement and expectation on CSD is low, it does not give negative effect on customer satisfaction even if it is fulfilled. But once it satisfies customers, the customer satisfaction can be increased.

(iv) Reverse CSD: Reverse CSD negatively effects on customer satisfaction when it is fulfilled while positively effect on customer satisfaction when it is not fulfilled.

(v) Indifferent CSD: Indifferent CSD doesn't influence on customer satisfaction in either ways because the degree of impact is not large enough.

The framework is composed of three main parts. In the first part, we extract CSDs from online reviews using LDA and customer sentiments toward each CSDs are determined by using BERT model. In the part 2, GBM is built to predict customer satisfaction using variables of sentiments on CSDs. Then SHAP which is one of statistical model explanation techniques is applied to explain GBM and measure the effect of each sentiment orientation with respect to CSDs. In the part 3, we classify and interpret CSDs in the point of business perspective using Kano model. The detail of the framework is illustrated in figure 1.

Figure 1. A framework for identifying customer satisfaction dimensions



3. Research Method

In this section, the process for modeling and analyzing customer satisfaction from online reviews is demonstrated, as shown in Figure 1. Each step in the framework is illustrated as below.

3.1 Mining customer's sentiments toward CSDs from online reviews

As online reviews are in the form of written words, they need natural language processing (NLP) to use reviews in business analysis (Cambria et al. 2017). In NLP, the unstructured data are transformed into the structured form that can be directly used for modelling customer satisfaction. In every step, different NLP methods appropriate to task objectives are utilized.

3.1.1. Extracting CSDs from online reviews based on LDA

First, Customer Satisfaction Dimensions (CSDs) need to be identified by classifying customers' main interests or topics in reviews. One of topic extraction methods called LDA (Latent Dirichlet Allocation) is used in this study. These topics can be viewed as CSDs (Bi et al., 2019; Tirunillai and Tellis, 2014; Guo, Barnes, and Jia, 2017). LDA is an unsupervised Bayesian probabilistic model which is mainly used to extract the latent topics from a large number of online reviews (Bi et al, 2019; Guo, Barnes, and Jia 2017; Blei, Ng, and Jordan, 2003; Tirunillai and Tellis, 2014). The topic in this study is regarded as a cluster of related words that represents one specific CSD. In the LDA model, each online review is regarded a mixed probability distribution of some topics in which customers are interested. And each topic has a unique probability distribution with specific words (Bi et al., 2019).

The details of mathematical principles and an algorithm used in this method are demonstrated in Blei, Ng, and Jordan (2003) and Hoffman, Blei, and Bach (2010) each.

There are several data preprocessing steps to extract product related topics. At first, all reviews are split into vocabulary level. Then some of irrelevant or noisy words such as stopwords, negation words and brand, product specific words are excluded for the effectiveness of extracting CSDs. Third, lemmatization is done which is the progress of unifying the inflected forms of a words to a single item to regard them as one identical input word in LDA. Fourth, the dictionary called corpus is created that contains every vocabulary in the cleansed review set.

Once LDA model is trained, the outputs are created composed of clusters of related words and their probability distributions. Topics with similar meanings were merged into same topic to compose reasonable topic list (Bi et al. 2019). Then clusters are labels as follows. $CSD = \{CSD_1, \ldots, CSD_i, \ldots . CSD_N\}, i \in \{1, 2, \ldots, N\}$. And sums of words' probability per topic list are calculated per sentence unit in every reviews. Then each sentence in each review's CSD is assigned according to the max sum value. $R_i = \{r_{i1}^l, \ldots\ldots, r_{ic}^k, \ldots\ldots, r_{iC_i}^g\}$, the set of reviews with respect to the CSD_i in the set of online reviews R is constructed where r_{ic}^k denotes the c^{th} review in R_i, the k^{th} review in R and C_i is the total number of reviews concerning the CSD_i, l, k, g $\in$ {1, 2, ⋯, M}.

3.1.2. Identifying the sentiment orientations of the reviews regarding each CSD using BERT

BERT (Bidirectional Encoder Representations from Transformers) is used to determine customer's sentiment orientation on each CSD. BERT is a state-of-the-art language representation model which is designed to pre-train deep bidirectional representations by jointly conditioning on both bidirectional context (Devlin et al. 2018). BERT is a verified pre-trained model that outperformances other pre−trained language models in eleven NLP tasks including sentence−level sentiment classification. Other than existing language models, BERT trains unstructured language data in both left and right context that allow pre−train model to successfully accomplish its task. The construct and principle of BERT is demonstrated on Devlin et al. (2018). Thus, BERT is used to classify each sentence's sentiment orientation in a review. In this study, transfer learning which uses pre−trained model on a different but similar problem was applied on sentiment classification.

Let denote S_{ik}^{*} as the sentiment orientation of CSD_i in online review k^th review in R, where $* \epsilon$ {POS, NEG}. S_{ik}^{*} is labeled nominally and Table 1 is designed with structured form of sentiment orientation in each CSD_i. If r_{ic}^{k} 's sentiment orientation is classified as positive, then S_{ik}^{POS} = 1 and S_{ik}^{NEG} = 0; else if r_{ic}^{k} 's sentiment orientation is classified as negative, then S_{ik}^{NEG} = 1 and S_{ik}^{POS} = 0; else if there is no response CSD_i in k's review, then both S_{ik}^{NEG} and S_{ik}^{POS} have the value of 0. Last, customer satisfaction (rating) is also labeled with integer numbers range from 1 to 5.

Table 1. Structure data of online reviews.

Online Review	CSD_1		CSD_2		· ·	CSD_N		Customer Rating
	S_{1k}^{POS}	S_{1k}^{NEG}	S_{2k}^{POS}	S_{2k}^{NEG}	· ·	S_{Nk}^{POS}	S_{Nk}^{NEG}	
r_1	1	0	0	0	· ·	0	0	5
r_2	0	0	0	1	· ·	0	1	2
· ·	· ·	· ·	· ·	· ·	· ·	· ·	· ·	· ·
r_M	0	1	0	0	· ·	1	0	4

3.2 Measuring the effects of customer sentiments toward each CSD on customer satisfaction

GBM (Gradient Boosting Machine) is applied to measure the effects of customer sentiments toward each CSD on rating (customer satisfaction). Boosting algorithm constructs and combines several simple models ('weak learner') with certain optimization method to establish a 'strong learner'. Then Friedman (2001) introduced GBM with a numerical optimization algorithm which has a purpose to find additive model minimizing the loss function. Friedman (2001) demonstrated GBM as one of powerful tree boost models that produces competitive, highly robust, and interpretable procedures for both regression and classification. GBM has been widely renowned in both academic and real-world problems (Chen and Guestrin, 2016; He et al., 2014). And it is also recognized that solutions using GBM beat other solutions using deep neural net based models in various challenges including store sales prediction, high energy physics event classification, customer behavior prediction, ad click through rate prediction, web text classification and so on (Chen and Guestrin, 2016). The key factor of GBM's outperformance is its scalability in all scenarios which explores ten times more scenarios than existing machine in same time. S_{ik}^{*}, Sentiment orientations toward each CSD and customer satisfaction value are put in training GBM so that the effects of customer sentiments about each CSD is able to be measured and predicted.

3.3 Identifying the feature of each CSD from the customer's perspective

SHAP (Shapley Additive Explanation)

These days, a lot of studies try to understand how a model works to correctly interpret the output model made (Bach et al., 2015; Ribeiro, Shrikumar et al. 2016; Shrikumar, Greenside, and

Kundaje, 2017; Singh, and Guestrin, 2016). As availability of big data set has increased, complex models have been preferred for high accuracy. However, due to their complicated structure and process, researchers encounter on a difficulty to fully interpret complex models. In this study, it is very critical to measure attributions of each CSD's sentiment feature to customer satisfaction in exploring dynamics of product dimensions in the point of customer.

Among interpretation methods such as LIME, LIFT, Layer-wise relevance propagation, SHAP (Shapley Additive Explanation) has been recognized with better consistency and human intuition (Lundberg and Lee, 2017, 2019). Moreover, SHAP values are consistent and locally accurate attribution values that measure feature importance. The process and mechanism of SHAP is illustrated as below.

(1) Additive Feature Attribution Methods

Instead of the original model, SHAP uses explanation model for ease of interpretability. Explanation model is a simpler model which is defined as 'any interpretable approximation of the original model' (Lundberg and Lee, 2017). Let denote f be the original model and g the explanation model which approximates the original model. Explanation model uses simplified inputs x' and mapping function $h_x(x') = x$ to map the original inputs. We designed local methods which try to explain output of $f(x)$ and local methods keep attempt to make of $f(z') \approx f(h_x(z'))$ whenever $z' \approx x'$.

Definition 1. Additive feature attribution methods have an explanation model g that is a linear function of binary variables:

$g(z') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i z'_i$ where $z' \in \{0, 1\}^M$, M is the number of simplified input features, and $\phi_i \in$ R.

The z'_i's value is 1 when a feature is observed whereas z'_i's value is 0 when a feature is unknown. The z'_i variables typically represent a feature being observed ($z'_i = 1$) or unknown ($z'_i = 0$), and $\emptyset_i$'s are the feature attribution values. Summing up all observed $\emptyset_i$'s values, it approximates the output of original model $f(x)$.

(2) Classic Shapley Value Estimation

The feature attribution value $\emptyset_i$ is based on Shapley regression value which represents feature importance for linear models with multicollinearity (Lipovetsky and Conklin, 2001). Let denote F is the set of all features and S is the values of the input features ($S \subseteq F$). In order to get Shapley regression values which are regarded as feature importance in this study, we compared two models $f_{S\cup\{i\}}(x_{S\cup\{i\}})$ and $f_S(x_S)$. A model with feature S^*_{1k} and another model without S^*_{1k} are trained. And we see difference of two model with all possible subsets $S \subseteq F \setminus \{i\}$. The Shapley values are computed by getting weighted average of all possible differences and used as the effect on the model prediction including certain feature.

$$\emptyset_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \left[f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)\right] \qquad (1)$$

(3) SHAP Values and Property

Lundberg (2017) define SHAP values as 'a conditional expectation function of the original model' where $f_x(z') = f(h_x(z')) = E[f(z)|Z_S]$, and S is the set of non−zero indexes in z'. SHAP is one of unique additive feature importance measurement that has three main properties (Local Accuracy, Missingness, Consistency) (Lundberg, 2017).

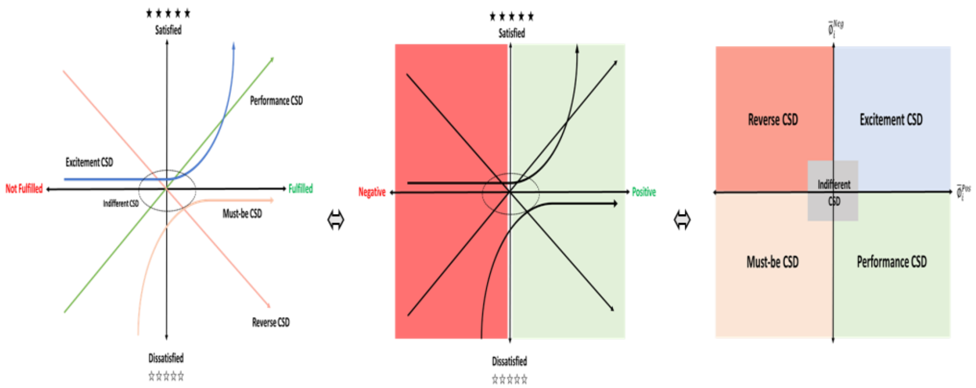
Local Accuracy implies the explanation model approximates the original model when $h_x(x') = x$. In terms of additive feature attributions, the sum of feature attribution approximates the model output. The second property, missingness states that missing features where $x'_i = 0$ don't give any influence on the model output ($\emptyset_i = 0$). The third property, consistency refers that the size of feature impact on the model will not be changed depending on model type.

To measure the attribution of each CSD's sentiments which are input set of GBM, we train the explanation model by putting all review samples. Then each feature's SHAP values is calculated that every observed sentiment orientation toward product's CSD can have its own SHAP value. In this study, we regard the SHAP value of j sentiment toward $\boldsymbol{CSD_i}$ as $\boldsymbol{\emptyset_{ij}}$. And we get it through the equation 2 as follows.

$$\emptyset_{i*j} = \sum_{S\subseteq F\setminus\{i*j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left[f_{S\cup\{i*j\}}\left(x_{S\cup\{i*j\}}\right) - f_S(x_S)\right]$$
$$, i \in \{1, 2, \ldots, N\}\ \mathit{and}\ j \in \{POS, NEG\} \qquad (2)$$

3.4 Classifying each CSD into Kano categories

Figure 2. The effect-based Kano model



Each CSD is identified with the obtained SHAP values $\boldsymbol{\emptyset_i}$ and an effect-based Kano model (EKM). In this study, i is the feature which represents the positive or negative sentiment orientation toward each CSD. The median $(\widetilde{\boldsymbol{\emptyset}}_{i*j})$ among all SHAP values of the sentiment toward $\boldsymbol{CSD_i}$ is used as representative feature attribution value. As different SHAP values are gotten according to the combination of CSDs observed, median less dependent on variance is appropriate to be used. The main principle of EKM is demonstrated as below.

EKM distinguishes Kano category base on CSD fulfillment and customer satisfaction. The positive sentiment is regarded as the success of CSD fulfillment whereas the negative sentiment is regarded as the failure of CSD fulfillment. Moreover, customer satisfaction is substituted to customer rating on a product.

In figure 2, the right side of the graph is the part of positive sentiment (fulfilled CSD) whereas the left side is the part of negative sentiment (unfulfilled CSD). So $\tilde{\emptyset}_{i*POS}$ is related with right side of the first and third quadrant of the graph whereas $\tilde{\emptyset}_{i*NEG}$ would be located on the second and fourth quadrant of the graph. Thus, $\tilde{\emptyset}_{i*POS}$ implies the amount of feature impact of CSD_i on overall customer satisfaction when it's fulfilled but $\tilde{\emptyset}_{i*NEG}$ is regarded as the amount of feature impact of CSD_i on overall customer satisfaction when it's not fulfilled. The specific meaning of $\tilde{\emptyset}_{i*POS}$ and $\tilde{\emptyset}_{i*NEG}$ is illustrated as follows.

(i) If $\tilde{\emptyset}_{i*POS} > 0$, the overall customer satisfaction level will increase as the customer's requirement about CSD_i is fulfilled.
(ii) If $\tilde{\emptyset}_{i*POS} \leq 0$, the overall customer satisfaction level will not increase as the customer's requirement about CSD_i is fulfilled.
(iii) If $\tilde{\emptyset}_{i*NEG} \geq 0$, the overall customer satisfaction level will not decrease as the customer's requirement about CSD_i is unfulfilled.
(iv) If $\tilde{\emptyset}_{i*NEG} < 0$, the overall customer satisfaction level will decrease as the customer's requirement about CSD_i is unfulfilled.

So the third graph in figure 2 shows Kano segment corresponding to the characteristic of SHAP values. The criteria of Kano category based on this graph is illustrated as follows.
(i) If $\tilde{\emptyset}_{i*POS} \leq 0$ and $\tilde{\emptyset}_{i*NEG} < 0$, then CSD_i is a must-be CSD.
(ii) If $\tilde{\emptyset}_{i*POS} \leq 0$ and $\tilde{\emptyset}_{i*NEG} \geq 0$, then CSD_i is a reverse CSD.
(iii) If $\tilde{\emptyset}_{i*POS} > 0$ and $\tilde{\emptyset}_{i*NEG} < 0$, then CSD_i is a performance CSD.
(iv) If $\tilde{\emptyset}_{i*POS} > 0$ and $\tilde{\emptyset}_{i*NEG} \geq 0$, then CSD_i is an excitement CSD.
(v) If both $|\tilde{\emptyset}_{i*POS}| < (\frac{1}{10} \times \mathrm{I})$ and $\tilde{\emptyset}_{i*NEG} < (\frac{1}{10} \times \mathrm{I})$, then CSD_i is an indifferent CSD as the effect of CSD_i on the overall customer

satisfaction is too small (Bi et al., 2019).

4. Empirical Study

In section 4, we discuss two customer satisfaction analyses (product line comparison and connected products comparison) with the proposed method. First, Kano category between smartphone product lines with same CSD are compared. Second, Kano categories of smartphone and smartwatch are identified and compared together. We used Colab environment with Python language.

4.1 Study 1

4.1.1 Data collection

In order to analyze smartphone customers' satisfaction, we collected 19,453 online reviews from Amazon.com, the largest E-commerce platform in the worldwide. We limited the range of customers who bought products within U.S.A market. Among 19,453 reviews, these were split into 91,365 sentences. The collected data contain 24 products with 3 major brands which take more than 70% market share in 2021 market. Those products were released from 2018 to 2021.

4.1.2. The process of customer satisfaction dimension modeling framework

As mentioned in the section 3.1.1, LDA was applied to extract smartphone CSDs from the set of online review. Before conducting LDA, the data was transformed into vocabulary level with lemmatization held. Then irrelevant and noisy words were excluded. Library Genism was used with the parameter set as: the number of topics = 20 and passes = 15. After merging similar topics, we obtained 15 types of smartphone CSD as shown in Table 2 with frequency of each CSD responded in a total review set.

Reviews were decomposed into sentence basis and their CSD was labeled.

Table 2. Identified smartphone CSDs and their responded frequencies.

CSD	Frequency	CSD	Frequency
Battery	9,782	System	1,127
Appearance	671	Screen	4,855
Recognition	3,455	Charger	1,174
Camera	1,118	Pen	4,569
Price	20,159	Seller	7,385
Warranty	1,096	Software	3,689
Communication	21,853	Feeling	6,634
Edition	3,009		

After that, each sentence's sentiment orientation was identified. BERT was used as a pre-trained model in the transfer learning. We adopted BERT model provided from Tensorflow. Regarding the train set, 10 people discriminated 2,000 reviews' sentiment (positive or negative) and 1,875 reviews were used as a train set which at least 8 people's answers were identical. Hyperparameters were determined by using Bayesian optimization hyperparameter tuning method as Batch size: 10, Learning rate: 0.001, Max Length: 128, Epoch: 4 (Sneok, Larochelle, and Adams, 2012). Obtaining sentiment toward every observed CSD, the data structure was transformed as like table 1. Validation loss and validation accuracy of the model was illustrated in table 3 with comparison of SVM and back propagation neural network (BPNN) with same measures. Even if SVM is an unsupervised learning method which Bi et al. (2019) adopted on classifying sentiment of smartphone online reviews, we extracted validation data to see the model performance.

Then, GBM was trained to see the effect of customer sentiments toward CSDs on customer satisfaction. One of GBM based models named XGBoost was applied on this analysis (Chen and Guestrin, 2016). Bayesian optimization hyperparameter tuning method was used as well (the number of estimators = 10,000, learning rate = 0.05, max depth = 8, subsample = 0.8, column sample by tree = 0.4). K Fold cross-validation was progressed simultaneously where K is 10. RMSE of the model with other comparative models within a same dataset is demonstrated in Table 3.

Table 3. The details of BERT model performance with comparative models.

Model Objective	Sentiment Orientation Classification		
Model Type	SVM	Back Propagation Neural Network	BERT
Learning Type	Unsupervised	Supervised	Supervised & Transfer
Validation Loss	0.233	0.226	0.112
Validation Accuracy	0.812	0.916	0.945

Table 4. The details of GBM model performance with comparative models.

Model Objective	Regression of Customer Satisfaction		
Model Type	Back Propagation Neural Network	Random Forest	Gradient Boosting Machine
Model Structure	Neural Network	Ensemble	Ensemble
Validation RMSE	1.105	0.773	0.403

When the original model to be explained was established, we trained an explanation model which explains the impact of features based on the equation 2. All online review set used in GBM was input in training an SHAP explanation model as well. So, every observed customer's response on each CSDs got their own SHAP values. And the medians of each feature were computed and used as benchmark of Kano category classification.

4.1.3 Result

(1) Comparison products across editions

As shown in table 5, Kano category of each CSDs is demonstrated with SHAP median values. It is clarified that CSD Battery, Appearance, Recognition, Price, Communication, Edition, System, Pen, Seller, Software and Feeling are regarded as Performance CSD whereas CSD Camera, Warranty, Screen, and Charger are identified as Must-be CSD. None of Excitement CSD, Rever CSD, Indifferent CSD were found. The result of this study and existing studies are shown in Table 5 which also figured out Kano category of smartphone products CSD. Bi et al. (2019), Xiao, Wei, and Dong (2016), and Qi et al. (2016) used online review to clarify CSD characteristics with their proposed method which is related to the method used in this study. The product lists between Bi et al. (2019) and this study have at least 2 years of release year gap.

4 CSDs are newly identified. Charger, a newcomer, is classified to Must-be CSD because manufacturers started to exclude a charger in a basic accessory list in which customers regard it as a basic requirement. And it is also found that 9 Kano categories of CSDs have been changed compared to CSDs from existing studies. Those are largely two cases (1. Excitement CSD → Performance CSD, 2. Performance CSD → Must-be CSD) which corresponds to our hypothesis.

As for recognition, it is regarded that fingerprint and facial recognition is no more unique technique that surprises customers. Moreover, screen from Performance to Must-be CSD is similar with recognition. As smartphone users enjoy various contents in a form of video, smartphone manufacturers are getting pressure to provide high quality of display performance to their customers. However, communication changed from Must-be CSD to Performance CSD. This is because over 40% of products we examined include 5G state-of-art technology which is assumed to be at least 5 times faster than 4G technology. But it was not classified to Excitement CSD as customers don't stand for slower service than 4G, in which their overall satisfaction would be decreased when communication service doesn't live up to customer expectation.

Table 5. SHAP median value and Kano category of smartphone CSDs

CSD	Sentiment Orientation	SHAP value	Kano Category	CSD	Sentiment Orientation	SHAP value	Kano Category
Battery	POS	0.191	Performance	System	POS	0.089	Performance
	NEG	-0.692			NEG	-0.706	
Appearance	POS	0.095	Performance	Screen	POS	-0.036	Must-be
	NEG	-0.477			NEG	-0.558	
Recognition	POS	0.002	Performance	Charger	POS	-0.054	Must-be
	NEG	-0.459			NEG	-0.419	
Camera	POS	-0.006	Must-be	Pen	POS	0.170	Performance
	NEG	-0.356			NEG	-0.226	
Price	POS	0.368	Performance	Seller	POS	0.247	Performance
	NEG	-1.086			NEG	-0.836	
Warranty	POS	-0.259	Must-be	Software	POS	0.117	Performance
	NEG	-0.874			NEG	-0.789	
Communication	POS	0.092	Performance	Feeling	POS	0.295	Performance
	NEG	-0.561			NEG	-0.628	
Edition	POS	0.178	Performance				
	NEG	-0.564					

Table 6. Kano category comparison of previous studies

CSD	Xiao, Wei, and Dong (2016)	Qi et al. (2016)	Bi et al. (2019)	The proposed Method
Battery	Excitement	Performance	Performance	Performance
Appearance	Divergent	Excitement	Performance	Performance
Recognition	–	–	Excitement	Performance
Camera	Performance	Must–be	Performance	Must–be
Price	Excitement	Excitement	Excitement	Performance
Warranty	–	–	–	Must–be
Communication	–	–	Must–be	Performance
Edition	–	Must–be	–	Performance
System	Excitement	Excitement	Excitement	Performance
Screen	Performance	Excitement	Performance	Must–be
Charger	–	–	–	Must–be
Pen	–	–	–	Performance
Seller	–	–	–	Performance
Software	Divergent	–	–	Performance
Feeling	–	Excitement	Excitement	Performance

(2) Comparison between product line

Furthermore, we compared Kano categories by product line (premium, standard, low) to see whether customers' requirement and expectation are different in the level of customer segmentation. SHAP values were separately computed from three newly built GBM models which are built with exclusively different product line online reviews. Each Kano categories by product line are shown in Table 7 and median SHAP values are demonstrated on Table 8 as well.

As shown in Table 7, the number of Must-be CSD are increased as the level of product is getting higher which implies that smartphone manufacturers successfully attracted customers who they targeted on. In low product line, only Charger is identified as Must-be CSD while others are Performance CSD. For the standard line, Appearance, Warranty, Screen and Charger are Must-be CSD while the others are Performance CSD. Customers in Standard group have higher expectation and requirement in Screen and Appearance than customers in low group. Last, Camera, Warranty, System, Screen and Charger are Must-be CSD in Premium line. The premium group are more focusing on Camera and System which are differentiated dimensions from Standard line. From the result, we found two insights of segment characteristics. Regarding standard group relative to premium group, it is assumed that they are not tech-savvy but pursue affective attribute like appearance. However, premium group is composed of tech-savvy customers who put importance on system and camera.

Table 7. Kano category comparison by smartphone product line

CSD	Kano Category			CSD	Kano Category		
	Premium	Standard	Low		Premium	Standard	Low
Battery	Performance	Performance	Performance	System	Must-be	Performance	Performance
Appearance	Performance	Must-be	Performance	Screen	Must-be	Must-be	Performance
Recognition	Performance	Performance	Performance	Charger	Must-be	Must-be	Must-be
Camera	Must-be	Performance	Performance	Pen	Performance	Performance	Performance
Price	Performance	Performance	Performance	Seller	Performance	Performance	Performance
Warranty	Must-be	Must-be	Performance	Software	Performance	Performance	Performance
Communication	Performance	Performance	Performance	Feeling	Performance	Performance	Performance
Edition	Performance	Performance	Performance				

Table 8. SHAP median values by smartphone product line

CSD	Sentiment Orientation	SHAP value			CSD	Sentiment Orientation	SHAP value		
		Premium	Standard	Low			Premium	Standard	Low
Battery	POS	0.12	0.15	0.17	System	POS	-0.09	0.08	0.05
	NEG	-0.58	-0.71	-0.52		NEG	-0.86	-0.59	-0.73
Appearance	POS	0.04	-0.03	0.12	Screen	POS	-0.18	-0.11	0.16
	NEG	-0.68	-0.53	-0.44		NEG	-0.67	-0.58	-0.47
Recognition	POS	0.01	0.05	0.00	Charger	POS	-0.13	-0.04	-0.05
	NEG	-0.44	-0.46	-0.35		NEG	-0.36	-0.57	-0.65
Camera	POS	-0.01	0.05	0.09	Pen	POS	0.02	0.16	0.24
	NEG	-0.44	-0.52	-0.45		NEG	-0.44	-0.17	-0.44
Price	POS	0.37	0.33	0.43	Seller	POS	0.33	0.22	0.27
	NEG	-1.19	-1.22	-1.04		NEG	-0.99	-0.79	-0.77
Warranty	POS	-0.48	-0.50	0.05	Software	POS	0.06	0.03	0.19
	NEG	-0.59	-0.84	-0.82		NEG	-0.33	-0.69	-0.50
Communication	POS	0.14	0.06	0.35	Feeling	POS	0.37	0.23	0.32
	NEG	-0.73	-0.52	-0.64		NEG	-0.88	-0.63	-0.49
Edition	POS	0.10	0.08	0.23					
	NEG	-0.71	-0.48	-0.53					

4.2 Study 2

4.2.1 Research Process

38,210 of smartwatch reviews (115,493 sentences) were also collected from Amazon.com within U.S.A. market. The reviews are composed of 17 types of products and 5 brands which occupy more than 60% of U.S.A smartwatch market share. Since measuring the effect of sentiment orientation toward each CSD on customer satisfaction is similar with the process progressed in Study 1, only model performances and result are illustrated.

The type of smartwatch CSD was determined by CSD shown in Table 9. It is found that smartwatch product has CSDs of battery, appearance, price, warranty, edition, screen, seller, software which are identical to smartphone CSDs meanwhile some of smartwatch CSDs are unique compared to smartphone CSDs (band, connection, time, health, waterproof, tracking). It implies that smartwatch customer's interests are overlapped due to their similar product characteristics but also include watch specific dimensions together. BERT model for classifying each CSD's showed similar performance with smartwatch's (Validation Loss : 0.098 , Validation Accuracy: 0.949). And GBM model's RMSE was 0.373. Then, SHAP values were computed from SHAP explanation model and medians of positive or negative sentiment toward each CSD were determined that identified Kano category of smartwatch CSDs in Table 10.

4.2.2 Comparison between smartphone Kano categories and smartwatch Kano categories

It is shown that band, appearance, tracking, and software are classified into Must-be CSD while connection, price, time, screen, health, waterproof, battery, warranty, and edition turn out to be Performance CSD. It is found that smartwatch customers regard smartwatch as one of fashion items considering that Band and Appearance is identified as Must-be CSD. Furthermore, it is noticeable that Tracking and Software are Must-be CSD which means that customers have high expectations on electronic equipment functions. And SHAP median values of positive sentiment toward connection related to connecting with other electronic device and health's are identified as 0.078 and 0.086 which are relatively small than other positive sentiment related SHAP values.

Table 9. Identified smartwatch CSDs and their responded

frequencies.

CSD	Total Frequency	CSD	Total Frequency
Band	4,705	Waterproof	4,374
Connection	7,760	Battery	18,217
Appearance	4,811	Tracking	6,901
Price	5,333	Warranty	11,595
Time	13,098	Edition	10,845
Screen	4,811	Software	5,910
Health	15,264		

Table 10. SHAP median value and Kano category of smartwatch CSDs

CSD	Sentiment Orientation	Shapley Value	Kano Category	CSD	Sentiment Orientation	Shapley Value	Kano Category
Band	POS	-0.244	Must-be	Waterproof	POS	0.154	Performance
	NEG	-1.285			NEG	-0.587	
Connection	POS	0.078	Performance	Battery	POS	0.148	Performance
	NEG	-0.635			NEG	-0.778	
Appearance	POS	-0.042	Must-be	Tracking	POS	-0.029	Must-be
	NEG	-0.593			NEG	-0.459	
Price	POS	0.092	Performance	Warranty	POS	0.123	Performance
	NEG	-0.480			NEG	-0.314	
Time	POS	0.159	Performance	Edition	POS	0.201	Performance
	NEG	-0.648			NEG	-0.850	
Screen	POS	0.148	Performance	Software	POS	-0.041	Must-be
	NEG	-0.596			NEG	-0.366	
Health	POS	0.086	Performance				
	NEG	-0.430					

5. Conclusion

This paper has 4 primary contributions. First, methodologically, well-established big data-based models (BERT, GBM) are applied on figuring out Kano categories. Two main models proved that their performances are better than comparative models' performance which also have been widely used in previous studies. Thus, the effect of customer sentiment toward each CSDs on customer satisfaction can be measured with high validity and reliability.

Second, this paper introduced SHAP concept which explains the importance of sentiment orientations toward each CSDs. SHAP method is based on theoretical base of Shapley value and appliable in any kind of simple or complex statistical model to measure feature importance. Furthermore, this paper suggested Kano category classification with SHAP values. We anticipate further studies to use SHAP in Kano category identification in various industry or product/service.

Third, this study investigated the change of smartphone users' expectation and requirement toward the product. It is found that no more CSD except communication refreshes customers expectation on a smartphone. It is necessary for not only academic field but also industry area to discover new dimensions that excites smartphone users.

Fourth, we provided business insight to smartphone manufacturers by clarifying CSDs by product line. We have seen that each customer group has different characteristics of CSD combination. It may give product development / enhancement guidance to manufacturers.

Fifth, we identified smartwatch customers' characteristics, in which they have both fashion-specific and watch-specific requirements together. Moreover, we suggested manufacturers to conduct customer segmentation in multi-product level that can maximize customer value.

However, this study also contains a limitation. In the study, customer's sentiment orientation toward CSD is classified in a binary way (positive or negative) which means the effect doesn't reflect the sentiment strength in customer satisfaction. If promising future studies consider sentiment strength in figuring out CSD fulfillment effect, the study will be able to find business insight in much dynamical way.

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국문 초록

최근 10년 간 온라인 쇼핑 산업의 성장으로 온라인 쇼핑몰 플랫폼에 온라인 리뷰 등 무한한 소비자 반응, 만족도 관련 정보가 생성되고 있다. 이에 많은 기업들과 학계에서 이를 활용하여 VoC (Voice of Customer)를 반영한 소비자 만족도 모델링을 시도하고 있다. 본 논문은 BERT, GBM, SHAP 등을 활용하여 카노 모델 (Kano Model)에 기반한 소비자 만족도 특성 (Customer Satisfaction Dimension)을 분류하고 각 특성의 소비자 요구 충족 여부가 소비자 만족도에 미치는 영향도를 측정한다. 본 논문의 방법론에 활용된 각 빅데이터 모델 성능과 선행 연구들에서 사용된 모델 성능을 직접 구현 및 비교하여, 본 논문에서 활용된 모델들의 정확성과 안정성을 보였다. 또한 해석적 머신러닝 기법인 SHAP를 도입하여, 카노 카테고리를 분류하는 통일된 분류 방식을 제안한다. 본 연구는 제시된 방법론을 통해 스마트폰 및 스마트워치 제품군을 대상으로 실증 연구를 진행하며, 산업계에 제품 개발 및 개선, 고객 세분화 전략 등 기업 의사결정 방향성에 유의미한 제언을 제시함으로써 본 방법론의 실용적 가치를 입증하였다.

주 요 어: 소비자 만족도, 스마트폰, 스마트워치, BERT (Bidirectional Encoder Representations from Transformers), 카노 모델, SHAP (SHapley Additive eXplanation)

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