



# Classification of Quality Factors for Kano Model Based on Online Reviews: A Case Study of Online Medical Care

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**Abstract.** In the traditional Kano model, the acquisition of quality factors is relatively subjective and the classification criteria are not accurate enough. Therefore, how to obtain quality factors objectively and achieve accurate classification of Kano model is an important research issue. This paper proposes a Kano model quality factor classification method for online reviews, which mainly obtains quality factors through LDA model, analyzes the emotional tendency of online reviews through BERT model, and classifies the quality factors obtained based on ordered logical regression and Kano model. According to the comments and emotional analysis results on different quality factors, the empirical research is carried out with the online medical service platform of “haodf.com” as an example. The quality factors of online medical service are divided into three categories: must-be quality, attractive quality and one-dimensional quality factor. The experimental results show that the classification of quality factors for Kano model based on online reviews can effectively extract the quality factor information in online medical service reviews, which has guiding significance for improving the classification method of quality factor for Kano model and improving the quality of online medical service.

**Keywords:** Kano model · Online medical treatment · Ordered Logical regression · Emotional analysis · LDA model

## 1 Introduction

Inspired by Herzberg’s two-factor theory, Japanese scholar Kano (1984) first proposed the concept of Kano model. The model considers that the cognition of product/service quality should adopt a two-dimensional model, that is, there is a nonlinear relationship between product/service quality factors and customer satisfaction. The model divides the product/service quality factors into five types: attractive, must-be, one-dimensional, indifference and reverse quality factors [1].

However, in the application practice of Kano model, the acquisition of quality factors is relatively subjective and classification criteria are not precise enough [2], which greatly affect the decision support role of Kano model. The main reasons are as follow: ① Kano

model is relatively subjective in obtaining quality factors. ② The questionnaire of Kano model has a large number of questions, takes a lot of time, and customers are easy to have problems in choosing, and it is difficult to reflect customers' real psychology [3]. ③ The final classification result of Kano model is inaccurate enough [2, 4].

In order to obtain the potential expression theme of customer online comments, Zhang Yanfeng (2020) [5] took a mobile phone online reviews as an example, obtained high-frequency words in customer online reviews through word frequency statistical analysis, and summarized the product features that customers focus on. Considering that keywords and related high word frequency statistics only focus on the content of online review text data from the perspective of vocabulary, and cannot measure the relationship between words, sentences and customer's potential meaning expression, its application range is greatly limited [6]. For this reason, some scholars have proposed that LDA model can use probability theory to deconstruct the complex relationship between words, sentences and topics, and can effectively mine the potential topics that customers pay attention to [7]. In order to deeply analyze the customer's emotional tendencies in online reviews, Anlu (2017) [8] obtained the emotional scores of relevant texts through the emotional dictionary, while Li Haojun (2022) [9] recognized the customer's emotional tendencies through the vectorization of the review text and combined the BERT model. It is worth noting that the BERT model, as a deep learning method, can greatly improve the efficiency of emotional analysis, and is also applicable to emotional analysis of short sentences or whole sentences.

To sum up, the research of many scholars has provided ideas for the objective classification of Kano model, but considering that the traditional Kano model essentially discusses the relationship between customer satisfaction and product/service quality factors, it is not only necessary to understand customer satisfaction from the customer perspective, but also need to classify according to the non-linear relationship, which is relatively complex. For this reason, this paper proposes the classification of quality factors for Kano model based on online reviews, aiming at the acquisition of quality factors is relatively subjective and inaccurate classification criteria.

## 2 Classification Process of Kano Model Quality Factors for Online Reviews

### 2.1 Acquisition of Quality Factors Based on LDA Model

The LDA model can effectively reflect the complex relationship between comments and topics, topics and words in online reviews, and has certain advantages for in-depth mining of customers' real needs [10]. Therefore, this paper uses LDA model to obtain the quality factors of online reviews. The probability publicity of LDA is shown in (1).

$$p(i|n) = \sum_l p(i|l) \times p(l|n) \quad (1)$$

where,  $i$  represents the number of words,  $n$  is the number of comments, and  $l$  is the number of topics.

The generation process of LDA model is shown in Fig. 1.

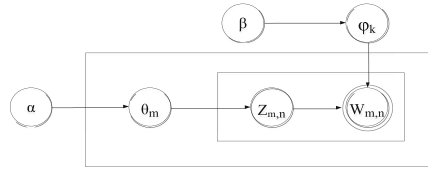


Fig. 1. Basic principle of LDA model

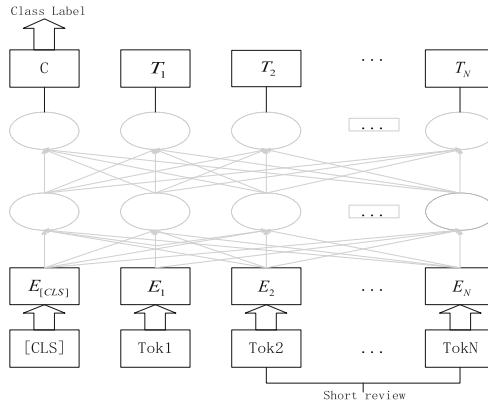


Fig. 2. The model of emotional classification

### 2.2 Analysis of Emotional Tendency Based on BERT Model

The BERT language model [11] was proposed by Devlin et al. in 2018. It is mainly based on the coder of Transformer architecture. The emotional analysis process of BERT model is mainly divided into two steps: comment segmentation and emotional analysis. In this paper, the BERT model is used to analyze the emotional tendency of the comments corresponding to the quality factors, and the emotional distribution of the quality factor term is statistically analyzed to obtain the positive and negative emotional tendencies under each quality factor classification.

The specific structure of the model is shown in Fig. 2.

### 2.3 Classification of Quality Factors for Kano Model Based on Ordered Logical Regression

Considering the advantages of the partial utility value function model in the joint analysis method, which is highly adaptable and consistent with the Kano model classification idea, this paper uses the partial utility value function model to measure the impact of quality factors on overall customer satisfaction [12]. The function model is as follow:

$$U = \alpha + \sum_{i=1}^n (\beta_i^{pos} X_i^{pos} + \beta_i^{neg} X_i^{neg}) \tag{2}$$

where, U represents the overall customer satisfaction, that is, the users' overall rating of the product/service quality in each review;  $\alpha$  is a constant;  $X_i^{pos}$  is the average positive

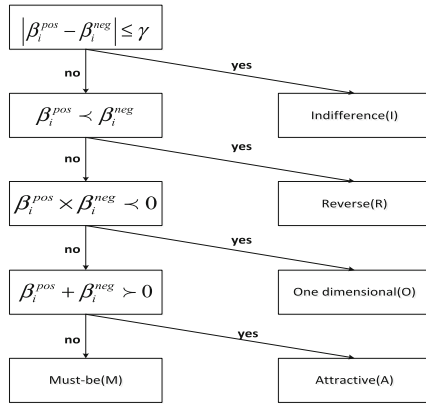


Fig. 3. Classification criteria of quality factors based on Kano model

emotional tendency of the *i*th quality factor,  $X_i^{neg}$  is the same; If the dimension is not involved in the comment, then  $X_i^{pos} = X_i^{neg} = 0$ ;  $\beta_i^{pos}$  and  $\beta_i^{neg}$  is the influence weight of the overall customer satisfaction score.

Due to the values of  $X_i^{pos}$  and  $X_i^{neg}$  are both 0 and 1, and they are ordered classification variables. Therefore, this paper estimates  $X_i^{pos}$  and  $X_i^{neg}$  in the abo formula by using the ordered logical regression method. The classification criteria is shown in Fig. 3.

### 3 Empirical Research: A Case Study of Online Medical Care

This paper selects the “haodf.com” medical service platform as the data source, and uses PyCharm2021.3.3 to crawl the evaluation data of the patients. The date is from January 1, 2019 to December 31, 2021. A total of 120098 reviews are crawled. By deleting duplicate and blank reviews, the number of remaining reviews is 46147. By using the “jieba” toolkit and using the degree of confusion to determine the optimal number of LDA topics, 10 topics were determined. The result is shown in Table 1.

According to the weight estimation method of quality factors, SPSS21.0 software was used to conduct ordered logical regression analysis on the patient evaluation data, and the parameter estimation of the impact of various online medical service quality factors was obtained, and the final classification results are shown in Table 2.

According to the classification results of Kano model, the following suggestions are obtained: ① Examine the professional knowledge level of doctors to ensure that doctors can effectively transform corresponding diseases from a large number of patient expressions. ② Urge doctors to study cases, improve their diagnostic ability, and encourage doctors to share their diagnostic experience of typical diseases. ③ The expression ability of doctors should be assessed to ensure that doctors can express complex pathological knowledge, treatment procedures and other information into popular sentences that patients can easily understand, so that patients can feel at ease. ④ Improve the ideological quality of doctors, and carry out regular ideological education and training and expansion activities. Optimize the service process and platform supervision mechanism, improve

**Table 1.** Factors of online medical service quality

Number	Quality factor	Quality factor expression
A <sub>1</sub>	High medical skill	Medical skill, skill, exquisite, superb, bright, professional
A <sub>2</sub>	Service attitude was friendly	Service attitude, enthusiastic, amiable, warm, kind
A <sub>3</sub>	Work conscientiously and responsibly	Conscientious, responsibility, dedicated, careful, meticulous, attentive
A <sub>4</sub>	Treatment plan is effective	Effect, treatment, recover, cure
A <sub>5</sub>	Accurate diagnosis	Accurate, diagnosis
A <sub>6</sub>	Questions and answers are detailed	Detailed, answer, explain
A <sub>7</sub>	Noble medical ethics	Medical ethics, noble, benevolence
A <sub>8</sub>	Provide humanistic care to patients	Care, look after
A <sub>9</sub>	Timely and effective communication	Communicate, consulting service, reply
A <sub>10</sub>	Trusted by patients	Trust, reassuring, worth recommending

**Table 2.** Parameter estimation and classification results of Kano model

Number	$\beta_i^{pos}$	$\beta_i^{neg}$	Quality factor classification
A <sub>1</sub>	-0.167	-2.243	M
A <sub>2</sub>	1.843	-2.559	O
A <sub>3</sub>	1.246	-0.643	O
A <sub>4</sub>	1.674	-1.696	O
A <sub>5</sub>	-0.496	-0.704	M
A <sub>6</sub>	-1.476	-1.576	M
A <sub>7</sub>	4.167	0.564	A
A <sub>8</sub>	0.192	0.058	A
A <sub>9</sub>	0.524	-2.997	O
A <sub>10</sub>	2.265	0.051	A

doctors' working attitude and service attitude, establish a civilized service model, and reduce doctors' personal bad feelings when providing services.

## 4 Conclusion

Aiming at the defects of inaccurate customer demand acquisition and subjective quality factor classification criteria in traditional Kano model, this paper attempts to build a Kano model quality factor classification method for online reviews, to obtain quality

factors from customer online reviews, and to transform the true feelings of customer evaluation through emotional analysis.

However, the research still has the following limitations: (1) BERT model is slower to train an epoch than traditional neural network under the same batch size parameter, and there may be some gap and mask character problems between the pre-training and the next task. (2) Choosing online medical services as the research object does not distinguish the direct purpose of patients' use of the platform.

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