Implementing Sentiment Analysis of Online Reviews to Improve Product and Customer Satisfaction: A QFD/ Kano Model Integration

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Implementing Sentiment Analysis of Online Reviews to Improve Product and Customer Satisfaction: A QFD/ Kano Model Integration

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Abstract

This study developed a Quality Function Deployment (QFD)/Kano model integration method for improving product development in terms of customer satisfaction by utilizing sentiment analysis as a Natural Language Processing (NLP) technique based on online reviews. This method is an alternative to traditional methods that rely on questionnaires and interviews to reduce costs and accelerate development. Instead of employing the QFD and Kano models independently, the integration technique produces findings almost immediately, utilizes thousands of evaluations and opinions at a cheap cost, and aids with decision-making issues. The data for this study were gathered from Amazon's enormous review database. Amazon dataset with 400,000 product ratings of Smartphone from June 2014 to December 2022 were used. The merging of two models has created new opportunities for Smartphone manufacturers in terms of deciding which technical specifications need to be modified and improved with customer satisfaction in mind. This could encourage companies to gradually heading towards the current approach that this research introduces, which makes it easier to gather feedback from a variety of customers in an affordable way.

Key words: Sentiment analysis; Natural Language Processing; Quality Function Deployment; Kano Model; Online Reviews.

Introduction

In a changing social, economic, and technical environment, businesses are now confronting more obstacles than ever in trying to satisfy the expectations of their more demanding customers. The Internet's quick expansion has made e-commerce—especially online shopping—extremely popular. A new statistical analysis reveals that an increasing number of customers choose to shop online at e-commerce sites like Amazon and eBay (Yan *et al*., 2017; Liu *et al*., 2021), therefore evaluating the usefulness of online reviews is crucial in the domains of information systems and e-commerce, as previous studies have shown that online reviews are more accurate than information from other sources (Qi *et al*., 2016). Despite relying on traditional methods of analysis, sentiment analysis is a rapidly expanding field of Natural Language Processing (NLP) used in a variety of fields such as politics and business (Khurana *et al.*, 2023). It is a popular strategy in analyzing e-commerce websites to extract customer emotions and comments from product-related reviews (Savici *et al*., 2023).

The integration between QFD and Kano model is regarded as an opportunity to improve the product in terms of consumer satisfaction, since continuous improvements in product features without regard for what customers genuinely desire may not result in increased levels of customer satisfaction (Chen *et al*., 2022).Where Quality function deployment (QFD) is a customer-driven quality management system that conveys customer requirements into technical specifications for various stages of production. In a world full of rivals QFD can have a substantial impact on a company's performance by incorporating customer needs at every stage of product development (Sullivan, 1986; Chan & Wu, 2002a). Additionally, Kano model introduce a qualitative technique for assessing how product feature performance affects customer satisfaction (Kano *et al.*, 1984).

This study incorporates these views and improves the integration of classic QFD and Kano model methods by employing advanced sentiment analysis techniques based on negative and positive reviews to assist in product development. This technique is meant to improve the efficiency and accuracy of product improvement operations at lower costs and accelerate development.

Sentiment Analysis as NLP Technique

Natural language processing (NLP) is a machine learning technology that enables computers to read, manipulate, and comprehend human language. It originated in the 1950s as a combination of AI and linguistics (Nadkarni *et al*., 2011).

NLP is an academic and technology-based research domain comprising a range of computational techniques for representation and automatic analysis of human languages; it is crucial for the vast amount of data on the Web, such as indexing, information retrieval, classification, extraction, translation, summarization, question-answering, and knowledge acquisition (Chowdhary & Chowdhary, 2020).

Sentiment analysis is a widely used approach in social media analysis. It enables the extraction of user emotions and the collecting of significant feedback from product-related comments (Savici *et al*., 2023). It, also known as opinion mining, assesses a community's feelings and opinions about a certain issue in order to identify their overall attitude (Petz *et al*., 2015).

Over twenty years ago, the study of sentiment analysis concerning online resources was conducted by Yi *et al*. (2003) when they extracted opinion about a subject from online text documents, meanwhile Dave *et al*. (2003) carried out one of the earliest investigations concerning product reviews since they used a sentiment classification along with a word classifier.

Hu & Liu (2004) followed previous effort using techniques from data mining and natural language processing to summarize product evaluations by presenting a feature-based overview of numerous client testimonials for an on-line product.Hu & Liu (2006) have complemented previous work by examining the issue of extracting and summarizing opinions in the context of product reviews that rely on web sources.

Gamon *et al.* (2005) and Popescu *et al*. (2007) addresses opinion summarization which consists of sentences from reviews that capture the author’s opinion witch interested in product features depending on extracting opinions from on-line customer's reviews by using information extraction system which mines reviews to build a model of important product features.

Effort of opinion summarization was completed by Chen & Lee (2011) Carenini *et al*. (2013) notwithstanding its advantages; the analysis of their findings reveals that the suggested method performs poorly on complicated statements including both positive and negative emotions. They recommended using additional NLP approaches in future studies.

In another context Na *et al*. (2010) address another aspect of sentiment analysis through examine the traits and variations in the expression of sentiment in movie reviews from four online opinion methods: discussion board threads, blog entries, user reviews, and critic reviews.

Wei *et al*. (2010), De Albornoz *et al*. (2011) and Lee & Bradlow (2011) use NLP techniques to estimate a product review's total score by analyzing consumer opinion on the many aspects of the product that are assessed. This approach looked into the most significant product features.

Fang & Zhan (2015) sought to address the issue of sentiment polarity categorization, which is one of the core challenges in sentiment analysis. Das *et al*. (2016) devised a probabilistic strategy for feature extraction at the word level, finding the related opinion word and generating feature-opinion pairs. They also developed an algorithm for detecting the ultimate polarity of opinions, assigning each pair to a cluster (positive, negative, or neutral).Additionally, Singla *et al.* (2017) address more than just the polarity issue, going beyond positive or negative emotion to incorporate a range of sentiments to assess the product holistically, allowing customers to make better decisions.

Ain *et al*. (2017) used sentiment analysis methodologies and deep learning models to overcome the lack of labeled data in natural language processing (NLP). Jagdale *et al*. (2019) used machine learning algorithms to classify reviews for smart devices; research results demonstrate the effectiveness of using machine learning techniques to evaluate product reviews. Furthermore, Yang *et al*. (2020) integrated Sentiment Lexicon with Deep Learning to address the inadequacies of the existing sentiment analysis model for product reviews.

Sentiment analysis was employed by Suresh *et al*. (2023) to forecast the product rating based on user input related to smart phones, which was obtained from Amazon.com. Asadabadi *et al*. (2023) employs advanced text mining to improve the accuracy of product evaluations (smart phone) and linked it to quality function deployment to guide product improvement efforts, Although previous studies dealt with product reviews, they focused on negative opinions rather than product enhancement. While negative impressions are important, it is critical to address customer positive impressions, which can guide us to improve product features, which is what this study attempts to do.

Quality function deployment

Quality function deployment (QFD) involves translating customer requirements into technical requirements for each stage of product development and production, including marketing, planning, design, engineering, prototype evaluation, production process development, and sales (Sullivan, 1986).

Akao, the originator of QFD, defines QFD as "a method for developing a design quality aimed at satisfying the customer and then translating the customer's demand into design targets and major quality assurance points to be used throughout the production phase" (Akao, 1990).

In an increasingly competitive world, QFD could mean the difference between success and failure (Mallon& Mulligan, 1993). It is a helpful instrument that can assist a business in transitioning to a proactive approach to product development. In order to increase customer satisfaction with the product, QFD is a customer-driven quality management system that integrates the "voice of the customer" (referred to customer requirements) into pertinent business needs at every stage of product development, from planning and process design to production and delivery (Chan & Wu, 2002a).

QFD system contains Four-Phase Model, also known as the Clausing model or the ASI (American Supplier Institute) model that divides a product development process as summarized by Cristiano *et al*. (2001) into four phases or steps using four matrices, first, house of quality, second, parts deployment, third, process planning, and fourth product planning

The first phase matching QFD matrix is referred to house of quality (HOQ) which involves gathering customer needs (WHATs) and converting them into technical measures (HOWs) such as product design specifications,

technical specifications, performance measures, and substitute quality attributes; the HOQ phase is crucial in the QFD method since it identifies consumer requirements and incorporates the producing company's competitive priorities to create technical measures (Chan & Wu, 2002b) as depicted in Figure 1.

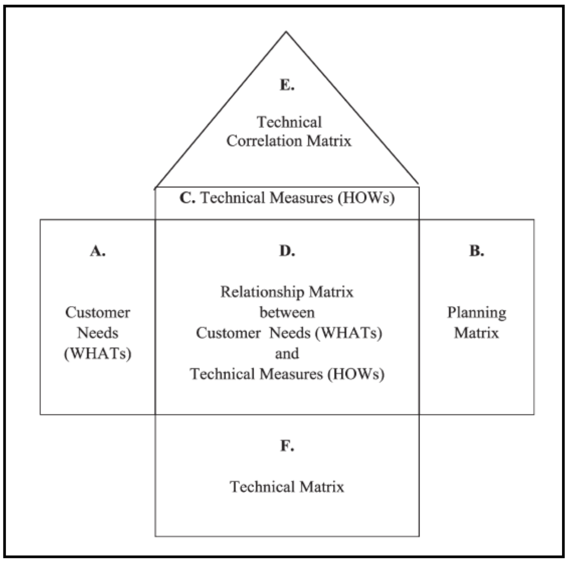

Figure (1): House of Quality (HOQ), adapted from (Chan & Wu, 2002b)

Customer requirements (Product Features)

QFD specializes in prioritizing customer requirements and integrating them throughout the product development process (Raharjo *et al.*, 2011).

Customer requirements can involve uncertainty and inaccurate nature (Abbaszadeh *et al.*, 2023). First, QFD has limitations in understanding and analyzing customer requirements fully (Xie *et al.*, 2023), so several research recommend using dynamic programming, analytical hierarchy process, and fuzzy logic to address these challenges (Zare Mehrjerdi, 2010), for instance Ayyildiz *et al*. (2023) employed Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP) integrated Quality Function Deployment technique through opinions of experts, and customers regarding the QFD application to meet customer expectations.

Furthermore, other research used artificial intelligence techniques to tackle with these issues, for instance, Mahardiningtyas & Qurtubi (2024) analyzing online data reviews through machine learning utilizing text processing, by integrating sentiment analysis into QFD support the product development process. In addition to Dadhich & Thankachan (2022) use Random Forest and K-Nearest Neighbor algorithms to address and examine the principles of automatic sentiment identification for Amazon and Flipkart products, categorizing comments into: neutral, negative, and favorable. They describe how their model can help with feature extraction and analyze a variety of reviews better than some other models.

Shen *et al.* (2022) present a full-process product improvement solution driven by online reviews, from the initial online review collection to the final technical specifications prioritization by combining fuzzy inference method, entropy-based synthesis evaluation method, and genetic algorithm back propagation neutral network through integrated quality function deployment-based strategy.

Kano Model

The Kano model is a qualitative method for evaluating the effect of attribute performance on customer satisfaction that was proposed by Kano *et al.* (1984). It divides attributes of products into five categories: one-dimensional, attractive, indifferent, must-be, and reverse as shown in figure (2). The assessment of these categories is based on the correlation between a quality attributes and the level of customer satisfaction (Chaudha *et al.*, 2011).

Must-be or basic quality element: Customers feel that this attribute is essential and will not be pleased if it is absent. Attractive quality element: in its absence, customers will still accept the product without being unhappy. In its presence, customers will be satisfied. One-dimensional aspect of quality: customer satisfaction is directly correlated with fulfillment level; higher fulfillment levels translate into higher customer satisfaction, and vice versa. Indifferent quality element: Whether or not this quality is offered, it will not have an impact on the satisfaction of the consumer. Reverse quality element: if this quality element is offered, buyers will not be happy; if not, they will be (Lee *et al.*, 2008).

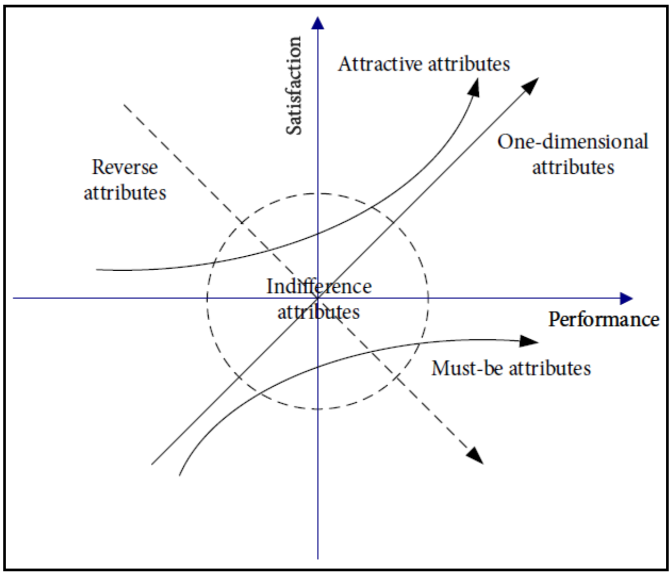

Figure (2): Kano model, adapted from (Zhao et al., 2021)

Zhang *et al.* (2018) used sentiment analysis with a fuzzy Kano model, offering a unique similarity measure approach with user preferences for a collaborative filtering algorithm to get users' various attitudes toward features of the product.

Bi *et al*. (2019) present a unique method for predicting customer satisfaction based on online reviews. A suggested method for modeling consumer happiness from online reviews combines aspect extraction, sentiment analysis, ensemble learning, neural networks, and the Kano model.

Chen *et al*. (2022) analyzed attribute directional performance by categorizing internet evaluations into positive and negative reviews. The Kano-IPA model was used to better understand consumer ratings and desires for hotel services.

Zhao *et al*. (2024) analyzed internet reviews to identify travelers' needs and improve hotel services. Specifically, this work creates a strength frequency Kano (SF-Kano) model to categorize the criteria indicated by travelers in online reviews.

Kano model and QFD Integration

Earlier, Matzler & Hinterhuber (1998) identified customer requirements and assigned priorities to them as a critical stage by integrating the Kano model with QFD. In order to precisely and thoroughly comprehend the nature of the customer requirements, Tan & Shen (2000) provide an integrated approach through including Kano's model into the QFD planning matrix.

Tontini (2007), employing a case study of product development by integrating the Kano model into the QFD, while Kuo *et al.* (2016) evaluated 27 service quality indicators by combining the QFD and Kano satisfaction models in order to develop solutions for improving service quality. Additionally, Priyono & Yulita (2017) use the integrated QFD and Kano Model to examine service qualities in a hospital front office and develop ways for improving them. WANG *et al.* (2023) develop an integrated model using the Kano model and QFD theory to evaluate the priority of interventions in enhancing the quality of physical examination.

Research gap and contribution to current knowledge

Previous research is divided into three distinct groups. The first group uses sentiment analysis techniques to extract information from internet resources. Although previous research (Ain *et al*., 2017; Yang *et al*., 2020; Suresh *et al*., 2023; Asadabadi *et al*., 2023) has addressed such techniques within a framework that serves e-commerce and businesses, employing them to extract customer opinions and trends, none of these studies have addressed linking these technologies with QFD or Kano models to extract customer opinions and harness them to develop product improvement procedures.

Although the second group of previous researches gathers customer information using traditional means such as surveys and interviews to obtain information from customers with the implementation of the QFD model (Dadhich & Thankachan, 2022; Shen *et al.*, 2022; Mahardiningtyas & Qurtubi, 2024) and Kano model (Zhang *et al*., 2018; Bi *et al*., 2019; Chen *et al*., 2022; Zhao *et al*., 2024) separately; but other researches in thr third group (Matzler & Hinterhuber, 1998; Tan & Shen, 2000; Tontini, 2007; Kuo *et al.*, 2016; WANG *et al.*, 2023) used integration of QFD/ Kano model based on using traditional methods to enhancing product development.

According to previous research, this study developed a QFD/Kano model integration approach to enhance product development processes focused on customer satisfaction using sentiment analysis as an NLP technique based on online reviews as an alternative to traditional methods that rely on questionnaires and interviews, resulting in an immediate and low-cost product improvement process.

Methodology

Sentiment Analysis and Kano Model / QFD Integration Framework

The proposed model suggests using sentiment to analyze Voice Of Customer (VOC) (customer requirements / Product features) as an alternative to questionnaires and interviews, by prioritizing these product features based on negative online reviews, additionally prioritizing technical specifications through QFD to improve the product, in contrast, extracting customer satisfaction through Kano model by analyzing positive and negative reviews to determine satisfaction level and integrating them to support competitive advantage for businesses

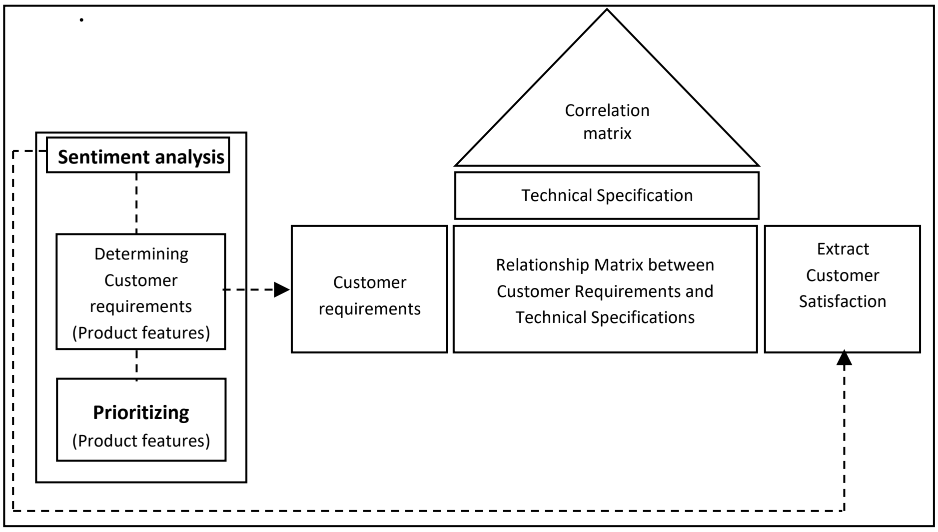

Figure (3): Proposed model for applying sentiment analysis to product improvement via QFD/Kano model integration.

Data collection

Data for this study were sourced from Amazon's massive review database. This study utilized an Amazon dataset containing 400,000 product reviews of Smart phones from June 2014 to December 2022.

Method

The process of HOQ manually displays the customer requirements, while the row at the bottom displays the importance weight of technical specifications (Yu and Kwak, 2015). It should be noted that the importance weight of each technical specifications for each customer requirements is determined by the column and row of the operation matrix by the following equation (Bottani, 2009).

$$RI_K = \sum_{j=1}^{m} Wj * \mathrm{R}_{jk} \quad k = 1, 2, \dots, p \qquad \text{.............................. (1)}$$

In previous equation, Wj and Rjk represent the important weight of customer requirements and the numerical value of the relationship between customer requirements and technical specifications in the operation matrix.

The next equation provides the relevance of each technical specification in the correlation matrix. Tkk' in this equation represents the correlation between each pair of technical specifications (Bottari, 2009).

$$Score_k = \mathrm{R}_k + \sum_{k' \neq k} \mathrm{T}_{kk'} . \mathrm{RI}_{k'} \quad k = 1, 2, \dots, p \qquad \text{...................... (2)}$$

After outlining the manual approach, the suggested model uses online product reviews to prioritize product features and technical specifications for product improvement. The framework is presented as follows:

Stage one: sentiment analysis of product features (customer requirements)

1- Defining a list of product features.
2- Standardize and integrate technical terms related to product features.
3- Cleansing and tokenizing reviews.

4- Implementing sentiment analysis to define product features using VADER software that called by python code [1].
5- Calculating product feature's weightings.

The study focuses on estimating the weightings of product features while considering the length and worth of the evaluations. Asadabadi *et al.* (2023) use equation (3) to analyze reviews with a decreasing rate of weightings dependent on the year in which the review is submitted, because the timing of a review is essential because customer preferences change over time, as seen with the evolution of mobile phones.

$$W_Y \left(\frac{1}{eNYD}\right)^{YD} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In equation (3), YD represents the distance between the year the review was written and the last year of the period. The "normalized year distance" (NYD) is calculated by dividing YD by the "last year minus the earliest year of the period. "e" can be replaced with values larger than "e" if the decision maker prioritizes recent years and considers older data is less relevant to their decision-making. Weighting loss for older data is decreased with values smaller than "e" and closer to one (but not below one). One might want to use the same weightings for all years. To consider all reviews, simply replace "e" in Equation (3) with one or eliminate the calculation entirely. This applies regardless of the year of posting.

6- Considering the effectiveness and Moderate the number of reviews.

Stage two: implementing QFD

This section computes a TSs priority list using the house of quality (HOQ) matrix. Either the positive or negative weightings of PFs, or both (as

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[1] VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool designed primarily for sentiments expressed on social media, but it also works well on texts from other domains. It is open-source software under the MIT license (https://github.com/cjhutto/vaderSentiment) that may be accessed via Python. It is based on lexicons of sentiment-related terms and uses the Amazon Mechanical Turk platform to score the positivity and negativity of word collections.

determined in stage One), can be used to compute the weightings of TSs. The QFD steps that follow are a modified version of the Asadabadi (2016) model.

i. Based on customer reviews, "m" in the below, matrix denotes the number of *PFs* and "a_i" the relative value of "i"th feature.

$$\begin{array}{cccc} PF1_1 & PF1_2 & \dots & PF1_m \end{array}$$
$$W_{PFS} = [a_1 \quad a_1 \quad \dots \quad a_m] \qquad \dots\dots\dots\dots\dots\dots\dots\dots(4)$$

$$TS \quad TS \quad TS \quad TS$$
$$W_{PF-TS} = \begin{array}{c} PF_1 \\ PF_2 \\ \vdots \\ PF_m \end{array} \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ b_{m1} & \dots & \dots & b_{mn} \end{bmatrix} \qquad \dots\dots\dots\dots\dots\dots\dots\dots(5)$$

ii. Creating the relationship matrix for Technical Specifications

Specialists are frequently able to complete the relationship matrix between *TSs*, namely $W_{TSs\text{-}TSs}$. Using pair wise comparisons, c*ij* represents how important "*i*"th *TS* is in comparison with "*j*"th *TS*.

$$TS \quad TS \quad TS \quad TS$$
$$W_{TS-TS} = \begin{array}{c} TS_1 \\ TS_2 \\ \vdots \\ TS_m \end{array} \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ c_{n1} & \dots & \dots & c_{nn} \end{bmatrix} \qquad \dots\dots\dots\dots\dots\dots\dots\dots(6)$$

iii. Multiplying matrix $W_{PFs\text{-}TSs}$ by $W_{TSs\text{-}TSs}$

$$W_{PFs-TSs-TSs} = \begin{array}{c} \\ PF_1 \\ PF_2 \\ \vdots \\ PF_m \end{array} \begin{array}{c} \begin{array}{cccc} TS & TS & TS & TS \end{array} \\ \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ b_{m1} & \dots & \dots & b_{mn} \end{bmatrix} \end{array} \times \begin{array}{c} \\ TS_1 \\ TS_2 \\ \vdots \\ TS_m \end{array} \begin{array}{c} \begin{array}{cccc} TS & TS & TS & TS \end{array} \\ \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ c_{n1} & \dots & \dots & c_{nn} \end{bmatrix} \end{array} \quad (7)$$

iv. Multiplying matrix W_{PFs} by $W_{PFs\text{-}TSs\text{-}TSs}$.
This step is determining the relations between PFs and ERs taking into account the interrelations between TSs. This matrix is labeled WPFs-TSs-TSs.

v. Matrix $W_{TSs\text{-}TSs}$ is multiplied by W_{TTSs}.
This step is to calculate the final priorities of TSs, namely W_{FTSs}.

$$WFTS_S = \begin{array}{c} \begin{array}{cccc} PF1_1 & PF1_2 & \dots & PF1_m \end{array} \\ [\begin{array}{cccc} a_1 & a_1 & \dots & a_m \end{array}] \end{array} \times W_{PFs-TSs-TSs} \quad \dots\dots\dots\dots\dots(8)$$

Stage three: implementing sentiment analysis to extract customer satisfaction through Kano model

Employ modified Kano model which is proposed by Zhao *et al.* (2021) based on the features of the three attribute categories in online reviews, with the impact degree of positive and negative feelings on customer overall usefulness, the influence index and satisfaction index are defined, depending on the following equations:

i. Customer overall usefulness:

$$y = \sum_{j=1}^{m} (\beta_j^{pos} \chi_j^{pos} + \beta_j^{neg} \chi_j^{neg}) + \alpha \quad \dots\dots\dots\dots..(9)$$

ii. Influence index:

$$\gamma_j = \sqrt{|\beta_j'^{pos}|^2 + |\beta_j'^{neg}|^2} \quad \dots\dots\dots \quad \dots\dots\dots\dots\dots(10)$$

iii. Satisfaction index:

$$\lambda = \frac{\beta'^{pos}_{j}}{|\beta'^{neg}_{j}|} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

Where β'^{pos}_{j} and β'^{neg}_{j} are standardized β^{pos}_{j} and β^{neg}_{j}

If λj < λ0, the feature is classified as undifferentiated. This feature's performance will have little impact on customer satisfaction; hence there is no need to classify it. If λj > λ0, the feature's performance has a considerable impact on customer satisfaction and should be distinguished. Three feature categories are classified based on the satisfaction index. **The first category is "Must-be" in this case,** customer rarely express **"Must-be"** features in online evaluations until they are dissatisfied, therefore negative feelings have a considerably greater impact on consumer total usefulness than positive sentiments do. λj > λ0 and λj < λ1 must be met, the second **category is "one-dimensional" in this case,** customer often frequently emphasize one-dimensional features in online reviews. Positive attitudes have a similar impact on customer total usefulness as negative ones do. The conditions λj > λ0 and λ1 < λj < λ2 must be met. **The third category is "Attractive"** which customer do not expect too much of, therefore good sentiments have a significantly greater impact on consumer total usefulness than negative sentiments. λj > λ0 and λj > λ2 must be met.

Stage four: integrating Kano model into QFD

Including Kano Model into QFD analysis by involving customer satisfaction index which extracted through equations 9, 10, and 11 and combining it with QFD matrix (matrix NO. 8) which represents a product features and technical specifications to determine which feature will be improved with regard of customer satisfaction.

Application using real-world example

Current researches (Suresh *et al*., 2022; Dieksona *et al*., 2023; Zhai *et al*., 2024) used Amazon data to explore customer reviews about Smartphone using sentiment analysis. This study used Amazon's enormous review database to obtain data. The Smartphone market has been flooded with billions of units. One challenge in this sector is integrating customer satisfaction with product features and technical specification. Amazon provides detailed product condition information for each cell phone, allowing for reliable classification of the cell phones, increasing the precision and dependability of study findings.

Stage one: sentiment analysis of product features (customer requirements)

A dataset of 400,000 product reviews of cell phones from June 2014 to December 2022 has been used from Amazon. The average rating was 3.79 and variance was 2.41.

1. Defining the list of product features by finding the number of appearances for each feature was found.
2. Cleansing and tokenizing reviews by using python code.
3. Implementing sentiment analysis to define product features using VADER software that called by python code utilizing Natural Language Toolkit (NLTK) libraries.
4. Using VADER software to calculate negative sentiments when each product features appears in the reviews.
5. Calculating the weightings of product features according to equation (3), the weights for each year are shown in table (2).

Stage two: QFD Implementation

1. ***Determining the inputs for the QFD method.***
   a. Number comments related to product features, table (1).
   b. Modifying number of reviews, table (3).
   c. The number of moderated reviews for each feature is multiplied by the weightings of the negative comments, table (4). The findings are then normalized (each weighting is divided by the total weighting), table (5).
   d. The outcomes of the preceding processes will be displayed in matrix (12), named W_{PFS}; these values represent customer opinions about product features.

Table (1) Product Features and related Number of Comments

Product Features	**Number of Comments**
Voice/sound	1
Memory	5,932
Camera	20,573
Screen	29,636
Weight	2,341
Battery	28,124
Siri	288
Charger	9,289
User friendly	701

Table (2) Weight of the Year

Year	**Weight of the Year**
2014	>0.001
2015	٠,٢٩
2016	٠,٤١
2017	٠,٤٤
2018	٠,٥٤
2019	٠,٦٩
2020	٠,٨٧
2021	٠,٩٢
2022	١

Table (3) Modified number of reviews

Product Features	**The moderated number of comments**
Voice/sound	0.000
Memory	0.016
Camera	0.074
Screen	0.205
Weight	0.003
Battery	0.211
Siri	0.006
Charger	0.052

User friendly	0.008

Modified negative reviews computed according to the following calculations:

Moderated Negative Reviews = (log number (reviews) * (negative reviews)

Where: β = (argmax (log number (reviews)))

Log Number (reviews) = log number (reviews) / β

Negative reviews = negative reviews / sum (negative reviews)

Table (4) Negative weights of product features

Product Features	Negative Weights
Voice/sound	0.000
Memory	0.041
Camera	0.047
Screen	0.049
Weight	0.037
Battery	0.048
Siri	0.027
Charger	0.043
User friendly	0.031

Table (5) weighting of product features after normalizing

Product Features	Normalized Negative Weights
Voice/sound	0.000
Memory	0.024
Camera	0.130
Screen	0.375
Weight	0.004
Battery	0.383
Siri	0.000
Charger	0.084
User friendly	0.000

$$W_{PFS} = \begin{array}{ccccccccc} \text{Voice /sound} & \text{Memory} & \text{Camera} & \text{Screen} & \text{Weight} & \text{battery} & \text{Siri} & \text{charger} & \text{User friendly} \\ [0.000 & 0.024 & 0.130 & 0.375 & 0.004 & 0.383 & 0.000 & 0.084 & 0.000] \end{array} \quad (12)$$

2. ***Applying relationship matrix***

Note that the relationship matrix utilizes a scale of zero to nine to determine how strong the link is between the elements of product features (e.g., camera) and the elements of technical specifications (e.g., hardware), with nine representing an "extremely strong relation".

Table (6) the relation between product feature and technical specifications

	Processor	Hardware	Software	Material	Design	Technology	Capacity	Security
voice/ sound	0	7	6	4	3	3	0	0
memory	8	5	5	1	0	4	8	1
camera	7	7	8	1	2	5	5	0
screen	2	5	7	7	5	5	1	0
weight	0	9	0	9	2	2	0	1
battery	1	0	1	0	1	8	0	0
Siri	0	0	6	0	0	4	0	6
charger	0	7	0	5	3	4	0	0
user friendly	6	5	8	0	5	6	0	0

3. Normalizing values

The values in Table (6) were derived and then normalized, as follows:

$$W_{PF-TS} = \begin{array}{l} \text{voice/ sound} \\ \text{memory} \\ \text{camera} \\ \text{screen} \\ \text{weight} \\ \text{battery} \\ \text{siri} \\ \text{charger} \\ \text{user friendly} \end{array} \begin{bmatrix} 0.000 & 0.304 & 0.261 & 0.174 & 0.130 & 0.130 & 0.000 \\ 0.250 & 0.156 & 0.156 & 0.031 & 0.000 & 0.125 & 0.250 \\ 0.200 & 0.200 & 0.229 & 0.029 & 0.057 & 0.143 & 0.143 \\ 0.063 & 0.156 & 0.229 & 0.219 & 0.156 & 0.156 & 0.031 \\ 0.000 & 0.391 & 0.000 & 0.391 & 0.087 & 0.087 & 0.000 \\ 0.091 & 0.000 & 0.091 & 0.000 & 0.091 & 0.727 & 0.000 \\ 0.000 & 0.000 & 0.375 & 0.000 & 0.000 & 0.250 & 0.000 \\ 0.000 & 0.368 & 0.000 & 0.263 & 0.158 & 0.211 & 0.000 \\ 0.200 & 0.167 & 0.267 & 0.000 & 0.167 & 0.200 & 0.000 \end{bmatrix}$$

4. Creating the relationship matrix among technical specifications TSs

Interrelations between *TSs* are calculated through pair-wise comparisons while the relationship matrix utilizes a scale of zero to nine to determine how strong the link is between the elements of product features (e.g., hardware) and the elements of technical specifications (e.g., capacity), with nine representing an "extremely strong relation".

Table (7) the relation amongst TSs

	Processor	Hardware	Software	Material	Design	Technology	Capacity	Security
Processor	1	6	3	9	6	5	9	4
Hardware	2	1	2	1	2	2	9	1
Software	1	6	1	8	1	5	5	7
Material	3	1	3	1	9	2	4	2
Design	3	1	3	2	1	2	2	1
Technology	3	6	1	1	3	1	1	4
Capacity	2	1	2	1	0	2	1	1
Security	2	2	5	2	0	4	0	1

5. *Normalizing values*

The values in Table (7) were derived and then normalized, as follows:

$$W_{TS-TS} = \begin{array}{l} \text{Processor} \\ \text{Hardware} \\ \text{Software} \\ \text{Material} \\ \text{Design} \\ \text{Technology} \\ \text{Capacity} \\ \text{Security} \end{array} \begin{bmatrix} 0.023 & 0.140 & 0.070 & 0.209 & 0.140 & 0.116 & 0.209 & 0.093 \\ 0.100 & 0.050 & 0.100 & 0.050 & 0.100 & 0.100 & 0.450 & 0.050 \\ 0.029 & 0.176 & 0.029 & 0.235 & 0.029 & 0.147 & 0.147 & 0.206 \\ 0.120 & 0.040 & 0.120 & 0.040 & 0.360 & 0.080 & 0.160 & 0.080 \\ 0.200 & 0.067 & 0.200 & 0.133 & 0.067 & 0.133 & 0.133 & 0.067 \\ 0.150 & 0.300 & 0.050 & 0.050 & 0.150 & 0.050 & 0.050 & 0.200 \\ 0.200 & 0.100 & 0.200 & 0.100 & 0.000 & 0.200 & 0.100 & 0.100 \\ 0.125 & 0.125 & 0.313 & 0.125 & 0.000 & 0.250 & 0.000 & 0.063 \end{bmatrix}$$

6. ***Multiplying Matrix $W_{PF\text{-}TS} \times W_{TS-TS}$***

$$W_{WPFs-TSs-TSs}\quad \begin{array}{l} \text{voice/sound} \\ \text{memory} \\ \text{camera} \\ \text{screen} \\ \text{weight} \\ \text{battery} \\ \text{Siri} \\ \text{charger} \\ \text{user friendly} \end{array} \begin{bmatrix} 0.104 & 0.116 & 0.091 & 0.107 & 0.129 & 0.106 & 0.227 & 0.118 \\ 0.102 & 0.138 & 0.107 & 0.133 & 0.085 & 0.134 & 0.182 & 0.118 \\ 0.096 & 0.140 & 0.091 & 0.136 & 0.090 & 0.123 & 0.199 & 0.125 \\ 0.110 & 0.124 & 0.098 & 0.113 & 0.143 & 0.107 & 0.182 & 0.121 \\ 0.122 & 0.072 & 0.121 & 0.056 & 0.199 & 0.097 & 0.254 & 0.077 \\ 0.132 & 0.253 & 0.064 & 0.089 & 0.131 & 0.072 & 0.081 & 0.179 \\ 0.095 & 0.188 & 0.141 & 0.148 & 0.048 & 0.161 & 0.068 & 0.151 \\ 0.132 & 0.103 & 0.111 & 0.060 & 0.174 & 0.089 & 0.239 & 0.092 \\ 0.092 & 0.155 & 0.082 & 0.145 & 0.094 & 0.111 & 0.188 & 0.133 \end{bmatrix} \quad (15)$$

7. ***Multiplying matrix W_{PFs} by $W_{PFs\text{-}ERs\text{-}ERs}$.***

$$\begin{array}{cccccccc} \text{Processor} & \text{Hardware} & \text{Software} & \text{Material} & \text{Design} & \text{Technology} & \text{Capacity} & \text{Security} \\ [0.036 & 0.047 & 0.032 & 0.035 & 0.040 & 0.035 & 0.057 & 0.040] \end{array} \quad (16)$$

This matrix indicates that the company manufacturing the phones should focus most of its resources and efforts on enhancing capacity. In the priority order, this technical specification (capacity) is followed by those about hardware, design, security, processor, material, technology, and software respectively.

Stage three: implementing sentiment analysis to extract customer satisfaction through Kano model

1. ***Determine the online reviews feature score***

The performance score of the feature is split into two categories: the positive sentiment performance score and the negative sentiment performance score, based on the customers' sentiments toward each feature in the single online review as depicted in table (8).

Table (8) Scores for each online review's features

Number	Voice/ sound		Memory		Camera		Screen		Weight		battery		Siri		charger		User friendly	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
1	0	0	0	0	0.4185	0	0.4185	0	0	0	0	0	0	0	0.4185	0	0.4185	0
2	0	0	0.125	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.262	0	0.262	0	0	0	0	0	0	0	0.262	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0.4289	0	0.4289	0	0.4289	0	0	0	0.4289	0	0	0	0.4289	0	0	0
⋮																		
281254	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

2. ***Applying a multiple linear regression method***
   Multiple linear regression method is utilized to identify the customer usefulness coefficients, and SPSS (Statistical Package for Social Science) is used to carry out the analysis according to equation (9) and result of this analysis is depicted in table (9).

Table (9) positive and negative influence degree of each feature

Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	charger	User friendly
β_j^{pos}	0.001	0.038	0.019	0.076	0.074	0.057	0.011	0.026	0.108
β_j^{neg}	-0.001	-0.021	-0.030	-0.089	-0.040	-0.059	-0.018	-0.012	-0.049

3. ***Normalization***
   The values that represent positive and negative influence degrees (β_j^{pos} and β_j^{neg}) of each feature in table (9) then normalized by dividing each value by the total value and final result is depicted in table (10).

Table (10) Normalization of positive and negative influence degree of each feature

Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	Charger	User friendly
β_i^{pos}	0.0024	0.0927	0.0463	0.1854	0.1805	0.139	0.0268	0.0634	0.2634
β_i^{neg}	0.0031	0.0658	0.094	0.279	0.1254	0.185	0.0564	0.0376	0.1536

4. ***Calculating influence and satisfaction index***
   The influence index and satisfaction index are defined according to equation (10) and (11); the result is shown in table (11) and (12).

Table (11) Influence index:

Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	Charger	User friendly
γ_j	0.004	0.1137	0.1048	0.335	0.2198	0.2314	0.0625	0.0737	0.3049

Table (12) Satisfaction index:

Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	Charger	User friendly
λ_j	0.778	1.4079	0.4928	0.6644	1.4394	0.7517	0.4755	1.6858	1.7149

Bi *et al.*, (2020) define feature classifications thresholds, the tenth of the maximum utility value is assumed to determine whether a feature is influential, i.e., $\gamma_j = 0.1$. The high and low thresholds of the satisfaction index are $\lambda_1 = 0.5$, $\lambda_2 = 1.7$. The classification results are as follows: Camera belongs to the must-be feature; Memory, Weight, Screen and battery belong to the one-dimensional features; User friendly is the attractive features; Voice /sound, Siri, Charger is the indifference features.

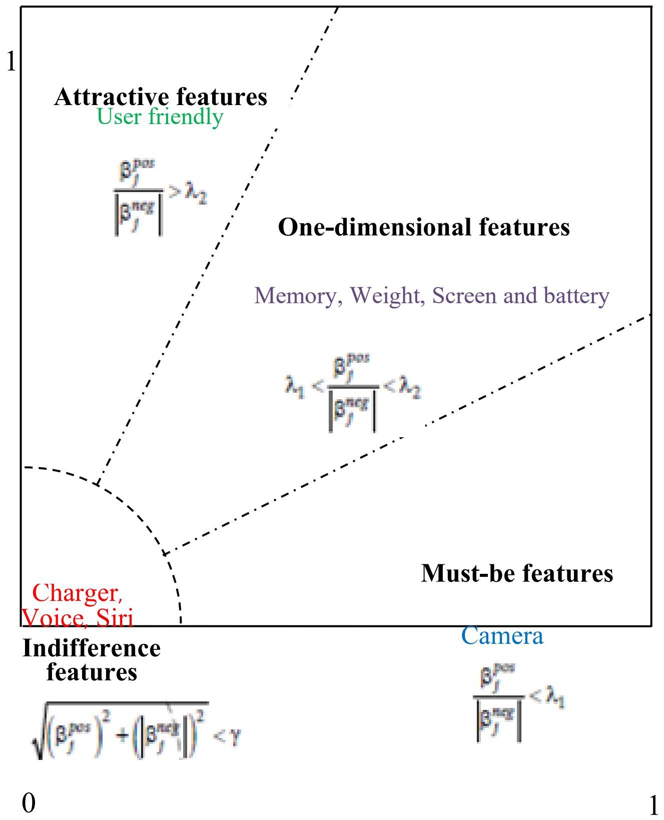

Figure (4): Product feature classification according to sentiment analysis

Stage four: integrating Kano model into QFD

Based on the previous stages which express the HOQ shape depicted in Figure (1), the first section of table (13) (QFD Technical Specifications) expressing the correlation matrix (the top of the house), which is based on the results of stage one and stage two through prioritizing customer requirements/product features (the left side of the house), which resulted in the formation of the relationship matrix (the middle side of the house). The second section of the table (13) (Kano model - Influence and Satisfaction Index) expresses the planning matrix, which has been replaced by extracting customer satisfaction based on stage three outcomes (the right side of the house). Finally Smartphone producers can use this integrated model to improve product with customer satisfaction in mind by simply apply the following steps:

Table (13) QFD/ Kano model integration table

QFD - Technical Specifications									
Technical Specifications	Processor	Hardware	Software	Material	Design	Technology	Capacity	Security	
	0.036	0.047	0.032	0.035	0.040	0.035	0.057	0.040	
Ranking	#5	#2	#8	#6	#3	#7	#1	#4	
Kano model - Influence and Satisfaction index									
Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	Charger	User friendly
γ_j	0.004	0.1137	0.1048	0.335	0.2198	0.2314	0.0625	0.0737	0.3049
Product features	Voice /sound	Memory	Camera	Screen	Weight	battery	Siri	Charger	User friendly
λ_j	0.778	1.4079	0.4928	0.6644	1.4394	0.7517	0.4755	1.6858	1.7149

1. Determining the priority of each technical specification depending on its ranking (descending), the biggest value (#1 in ranking) is the most technical specification need to be improved.
2. Determining satisfaction level for each feature by :
   i. Check the values that belong to influence index to determine Indifference features (red colored).
   ii. Check the values that belong to satisfaction index to determine must-be (blue colored), one-dimensional (purple colored), and attractive features (green colored).

Discussion

The primary result of this study is a novel approach to integrating a QFD/Kano model to enhance product development regards to customer satisfaction using sentiment analysis as an NLP technique based on online reviews, which has been directly validated through the application of research methodology.

This study uses a Python code in the QFD model at several stages to extract and analyze positive and negative reviews using VADER software (Valence Aware Dictionary and Sentiment Reasoner), which is a lexicon and rule-based sentiment analysis tool aimed primarily at sentiments expressed on social media, but it also works well on texts from other domains.

Furthermore, to estimate customer satisfaction levels, the study used Python code, MS Excel, and SPSS to extract and analyze customer comments from online resources using the Kano model.

The QFD model was implemented using certain processes, the first of which was defining the list of product features by determining how many times each feature appeared. Results would be more realistic if the time factor was taken into consideration when calculating the weightings of product attributes.

Sentiment analysis was utilized to apply the Kano model to obtain consumer satisfaction by Find the feature score that internet reviews usually have. Customers' opinions about each feature in a single online review are used to divide the feature's performance score into two categories: the positive sentiment performance score and the negative sentiment performance score.

Using both positive and negative reviews is one of the study's biggest challenges with our suggestions because, while negative reviews can be used to improve the way products are developed, they can also be used in conjunction with positive reviews to determine how satisfied customers are. This study uses sentiment analysis to collect negative opinions about products, which are then fed into a QFD model based on product features and technical specifications, and translated to improve the product process. On the other hand, the study uses sentiment analysis to extract both positive and negative comments to estimate the level of consumer satisfaction using Kano model.

The findings demonstrated that the company that manufactures Smartphone should focus most of its resources and efforts on improving the Smartphone capacity. These technical specifications are followed by other technical specifications in the priority list, including hardware, design, security, processor, material, technology, and finally software.

Although the results showed the ranking of all technical specifications, they also revealed that the capacity feature is the most in need of support and development by Smartphone manufacturers, as it is the primary cause of consumer dissatisfaction. However, reading this result may be tainted with some ambiguity, highlighting the need for integration between the Kano model and QFD, as the Kano model explains which of the product features fall within the various levels of customer satisfaction. As shown by the results, the Camera falls under Must-be, indicating that customers believe this feature is essential and will be dissatisfied if it is missing. Furthermore, the User-friendly is located in the Attractive quality element, implying that despite its absence, customers will accept the product without being dissatisfied. Furthermore, all features, including memory, weight, screen, and battery, fall under the one-dimensional, which means that customer satisfaction is directly tied to fulfillment level; better fulfillment levels translate into higher customer satisfaction, and vice versa. Finally, Charger, Voice, and Siri are Indifference features, which indicate that whether or not these qualities are available will not affect customer satisfaction.

Smartphone producers can use this integrated model to improve products with customer satisfaction by determining the priority of each technical specification based on its ranking. The biggest value indicates the most technical specification needing improvement. The satisfaction level for each feature is determined by checking the influence index values to determine Indifference features, and satisfaction index values to determine must-be, one-dimensional, and attractive features. Where The QFD model, based on HOQ shape, consists of two sections: QFD Technical Specifications and Kano model - Influence and Satisfaction Index. The first section consists of a correlation matrix, based on customer requirements and product features, and a relationship matrix. The second section, Kano model - Influence and Satisfaction Index, extracts customer satisfaction based on stage three outcomes.

The study determines which product characteristics buyers value most and how pleased they are with the features that are already there by looking at product reviews on Amazon.com. For a wide range of goods, including cell phones and electronics, Amazon is a trustworthy supplier. It is renowned for having in-depth evaluations and reviews of products. Thus, it makes sense to rely on its data to gather consumer preferences and views on different product characteristics and then use that information to weight the needs of the customer. Using this method, a prioritized list of Product features is produced that is derived from thousands of evaluations authored by experts rather than a small sample of interviews and surveys.

This study additionally suggests a quick, resource-saving method that covers a large client base, increases accuracy, and uses fewer resources. By doing away with worries about the amount of time needed for data collection and analysis, this approach guarantees that the process of improving products is efficient and relevant due to customer changes or new needs, where using QFD and Kano model integration for future improvement procedures might not be applicable due to information gathering and analysis done by hand might take a long time, particularly for big client groups.

Conclusion

This study established a QFD/Kano model integration method for improving product development in terms of customer satisfaction using sentiment analysis as an NLP technique based on online reviews, which is an alternative to traditional methods that rely on questionnaires and interviews to reduce costs and speed up development.

Rather than using the QFD and Kano models separately, the integration technique can produce results almost instantaneously, leverage thousands of evaluations and opinions at a low cost, and assist with decision-making challenges.

Data for this study were sourced from Amazon's massive review database. This study utilized an Amazon dataset containing 400,000 product reviews of Smart phones from June 2014 to December 2022.The study proposed a model that utilized NLP sentiment analysis with QFD model with Kano model to create a more sophisticated approach that can analyze online data and identify areas where the production process needs to be improved.

The combination of two models has opened up new frontiers for Smartphone producers in terms of properly determining which technical specifications need to be adjusted and improved with customer satisfaction in mind. This could encourage companies to gradually move away from traditional methods (interviews and surveys) and heading towards the current approach that this research introduces, which makes it easier to gather feedback from a variety of customers in an affordable way.

Managerial implications

According to this research, decision-makers, managers, and manufacturers should make use of the following benefits:

This technique provides managers and decision-makers with a prioritized list of product features concerning their consumers based on the opinions of thousands of customers while requiring little resources by automatically performing sentiment analysis on customer reviews.

This approach provides manufacturers with a low-cost and convenient option to organize improvement processes. Because the main issue in quality management is that consumer' perceptions can change over time, resulting in outdated knowledge in future improvement efforts. Therefore the proposed solution requires few resources and can be repeated as needed.

This technique assists production managers in improving accuracy, conserving resources, reaching a wide range of customers, and reducing concerns about the time required to collect and analyze data in the product improvement process. Organizations can use online reviews to better understand and fulfill customer needs, resulting in more effective product improvement initiatives.

Limitation and Future research

The research relied on evaluating negative and positive reviews, while both types of reviews were used; the use of positive reviews was limited to determining the level of customer satisfaction using only the Kano model, opening the possibility of future research on positive reviews using the QFD model.

When using the Kano model, customer satisfaction was divided into three levels of quality elements (must-be, attractive, and one-dimensional) out of a total of five quality levels, giving researchers the opportunity to investigate the entire list of quality elements and demonstrate deeper expressions of customer satisfaction.

Another research opportunity is to use other NLP-related artificial intelligence models to shorten the steps of integrating between the two models (QFD model with Kano model), such as using LDA (Latent Dirichlet Allocation) algorithm to extract latent topics related to online reviews in order to achieve product improvement and customer satisfaction in unified steps. It is also possible to apply steps to investigate a type of product other than the Smartphone and compare the results in the future, taking into account the features of the different products as well as providing working groups of specialists to provide values to evaluate the relationship between the product's features and its technical specifications.

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تطبيق تحليل الآراء للمراجعات عبر الإنترنت لتحسين المنتج ورضا العملاء

التكامل بين نموذج كانو / نشر وظيفة الجودة

المستخلص

طورت هذه الدراسة طريقة دمج نموذج كانو / نشر وظيفة الجودة QFD)/Kano model) لتحسين تطوير المنتج بالنظر إلى رضا العملاء من خلال استخدام تحليل الآراء sentiment analysis كتقنية لمعالجة اللغة الطبيعية (NLP) تعتمد على المراجعات عبر الإنترنت. تعد هذه الطريقة بديلاً للطرق التقليدية التي تعتمد على الاستبيانات والمقابلات بهدف تقليل التكاليف وتسريع التطوير. بدلاً من استخدام نموذجي كانو ونشر وظيفة الجودة بشكل مستقل، تنتج هذه التقنية نتائج فورية تقريبًا، وتستخدم آلاف التقييمات والآراء بتكلفة رخيصة، وتساعد في قضايا اتخاذ القرار. تم جمع البيانات لهذه الدراسة من قاعدة بيانات المراجعات الضخمة لشركة Amazon. تم استخدام مجموعة بيانات Amazon التي تحتوي على ٤٠٠٠٠٠ تقييم لمنتج الهواتف الذكية من يونيو ٢٠١٤ إلى ديسمبر ٢٠٢٢. أدى دمج النموذجين إلى خلق فرص جديدة لمصنعي الهواتف الذكية من حيث تحديد المواصفات الفنية التي تحتاج إلى تعديل وتحسين مع وضع رضا العملاء في الاعتبار. وقد يشجع هذا الشركات على التوجه تدريجيًا نحو الطريقة الحالية التي يقدمها هذا البحث، والتي تجعل من السهل جمع الملاحظات من مجموعة متنوعة من العملاء بطريقة منخفضة التكلفة.

الكلمات المفتاحية: تحليل الآراء؛ معالجة اللغة الطبيعية؛ نشر وظيفة الجودة؛ نموذج كانو؛ المراجعات عبر الإنترنت.