



Article

Dynamic Mining of Consumer Demand via Online Hotel Reviews: A Hybrid Method

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Abstract: This study aims to dynamically mine the demands of hotel consumers. A total of 378,270 online reviews in the cities of Beijing, Chengdu, and Guangzhou in China were crawled using Python. Natural language processing (e.g., opinion mining and the BERT model) and an improved Kano model (containing One-dimensional, Attractive, Indifferent, and Must-be) were utilised to analyse online hotel reviews. The results indicate that the hotel attributes that consumers care about (e.g., Clean, Breakfast, and Front Desk) are dynamically fluctuating, and the attention and satisfaction of corresponding attributes will also change. This study classified consumer demand into eight types across cities and found that it changes over time. In addition, we also found that hotel attributes, satisfaction and attention, and consumer demands vary among different cities. Existing studies of capturing consumer demand are usually time-consuming and static, and the results are subjective. This study compared and analysed the consumer demands of hotels in different cities via a dynamic perspective, and used hybrid methods to improve the granularity of the analysis, expanding the general applicability of the Kano model. Hotel managers can refer to the results of this article to allocate resources for improvement and create competitive hotel services.

Keywords: dynamic mining; consumer demand; online hotel reviews; improved Kano model; natural language processing



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1. Introduction

In recent years, capturing consumer demand has become an important way for businesses to improve services and gain competitiveness, especially in the resource-limited and fragile hotel industry [1–3]. Consumers' demands consist of multiple attributes of products/services [4,5], such as location, cleanliness, service, and value for money [6]. Hence, businesses that want to mine consumer demand must understand customer expectations and emotional evaluations from online reviews [7]. However, hoteliers who simply improve certain service attributes for consumer satisfaction do not ensure that customer demands are met; doing so may even lead to service redundancy or wasted resources [8–10]. Therefore, it is critical for hotel development to explore consumers' demands in a more granular way and rationalise marketing or investment strategies.

The Kano model is a particularly useful tool for classifying and prioritising consumer demands [11]. It analyses the impact of consumer demands on consumer satisfaction, reflecting the nonlinear relationship between product performance and consumer satisfaction [12]. This model was inspired by dual-factor theory [13], which suggests that different service attributes have different effects on customer satisfaction/dissatisfaction [14]. According to Sven-Olaf Gerdt and Schewe (2019) [15], based on the Kano model, we should consider both the attributes of consumer satisfaction/dissatisfaction and the quality of the experience rather than limiting it to a satisfactory experience. For example, online reviews usually have dual valences; that is, even if certain attribute characteristics do not meet

customer expectations, customers are still satisfied with the hotel because of other well-performing attributes [16–18]. However, the original Kano model analyses consumers' attitudes towards different demands through questionnaires, interviews, evaluation methods, and other methods [19–22] rather than through direct quantitative analysis, and the results of demand classification are also time-consuming and subjective.

Subsequently, many scholars have integrated improved Kano models with natural language processing (NLP) techniques (e.g., opinion mining) to achieve quantitative calculations [14,20,23]. Some studies have compared changes in the content of online reviews before, during, and after the pandemic. However, these studies only consider the frequency of demand [24,25] and do not fully consider the intensity of demand (e.g., satisfaction and attention), which may bias the analysis results [26]. In addition, scholars usually study hotel reviews from different cities as a whole, ignoring the impact of regional differences on consumer demand [27]. The impact of regional differences on consumer demand has not been fully explored. Although many scholars have considered the time factor to analyse trends in sentiment in online reviews [28], they have mostly adopted a static perspective, thereby neglecting how consumer demand changes over time [2]. Therefore, it is particularly important to dynamically mine consumer demand using a hybrid method.

This study proposes a novel framework to effectively and dynamically mine consumer demand in a more fine-grained way. We compared the differences in hotel consumer demand in different cities, compensated for the limitations of previous static data analysis, and applied various advanced methods (e.g., NLP technology, Origin) to expand the applicability of the Kano model. Among them, NLP technology can perform opinion mining on online comments (such as attribute extraction and semantic association analysis), while Origin can achieve dynamic visualisation analysis. Furthermore, more accurate and dynamic detection of changes in consumer demand helps hoteliers determine resource allocation and improve service. The following questions are addressed in this article: (1) What consumer demands and corresponding hotel attributes are reflected in online reviews? (2) How can the satisfaction and attention level of consumer demands be determined and make a reasonable classification? (3) How can we dynamically analyse changes in consumer demand?

2. Literature Review

2.1. Online Hotel Reviews

Online hotel reviews are customers' evaluations of hotel service quality expectations and actual experiences [29]. Online reviews are becoming increasingly representative and crucial data sources due to their large scale, low cost, easy accessibility, objectivity, and reliability [30–34]. These reviews can help hoteliers understand consumers' attitudes, opinions, and satisfaction [35–37]. For example, scholars have used the relationship between attributes in online reviews and customer satisfaction/dissatisfaction to prioritise hotel service improvements [14,38–40]. Such research has informed scholars' efforts to uncover the value of online reviews from a dynamic perspective [2]. In fact, online reviews have become an important decision-making cue for consumers searching for hotels to book [41] and play a pivotal role in hotel occupancy rates [42,43]. Accordingly, online reviews provide a unique perspective that helps hotel operators mine consumer demand and enhance hotel competitiveness.

2.2. Consumer Demand and Opinion Mining

2.2.1. Consumer Demand

Consumer demand is the sum of the consumer's requirements and desires for a variety of information and related services; it is a critical factor that influences hotel revenue management and the value judgments and preferences of users [44]. Typically, consumer demand includes multiple product/service attributes [2,45], and customers show different preferences for different attributes [7,46]. Some scholars have discovered that the importance of hotel attributes for customer satisfaction can change depending on regional

variances [25,27], unexpected events (e.g., COVID-19), or seasonal factors [47–49]. Accordingly, consumer demand is characterised by ambiguity, dynamism, similarity, cyclicity, and uncertainty [50]. However, although consumer demand is a dynamic concept, studies have mostly used static data in their analyses [2]. Therefore, it is particularly important to classify service quality attributes from a dynamic perspective and to explore the evolutionary trends in consumer demand.

2.2.2. Opinion Mining

Opinion mining can quantify online reviews via NLP, mainly through attribute extraction and sentiment analysis [31,51–53]. In hospitality research, attribute extraction is the basis for sentiment analysis. Attribute extraction has been widely utilised to mine consumer preferences from the exponentially growing amount of user-generated content [54]. Common methods include LDA topic modelling tools [55,56], word frequency inverse document frequency (TF-IDF) and Word2Vec methods [57], and syntactic analysis [58]. Although attribute mining is useful for identifying key service factors, it does not reflect whether customers are satisfied with hotel service quality [14,59]. Sentiment analysis is the basis for mining product attributes for implied customer demands [31,60]. It uses various NLP techniques to extract sentiments expressed in review texts, such as emotions (e.g., anger and happiness) and polarity (e.g., positive, negative, and neutral) [61]. Sentiment analysis can be divided into machine learning methods (naive Bayes, maximum entropy, and support vector machines) [62] and lexicon-based approaches (e.g., lexicon-based and corpus-based methods) [31,61]. Nevertheless, both methods involve coarse-grained analyses; they cannot capture the sentiment of entities and related aspects or concepts [60]. Fine-grained sentiment analysis is often referred to as aspect-based opinion mining, and its basic tasks include aspect extraction, opinion identification, and sentiment classification [63].

However, previous studies using opinion mining have mainly measured consumer sentiment, experiences, and service quality [64], such as by focusing on product feature preferences [58] or consumer satisfaction [65,66]. Hence, these deep learning-based studies have not clearly explained the relationship between consumer demands and satisfaction [67]. Chen et al. (2022) [67] and Bian et al. (2022) [7] suggested that attribute extraction and sentiment analysis can be integrated. Consequently, it is necessary to introduce novel research models to reveal the relationship between product/service attributes and sentiment tendencies to determine consumer demand.

2.3. Kano Model

As a popular satisfaction theory, the Kano model captures the nonlinear and asymmetric relationship between quality attributes and user satisfaction [68]. Kano (1984) [11] suggested that consumers have different attitudes toward different product attributes because different product attributes have different effects on consumer satisfaction, in line with dual-factor theory [13,14]. Therefore, Kano's model can be used to explore the relationship between consumer demands and satisfaction, classify product/service attributes and solve the problem of demand positioning [12,69,70]. In general, the Kano model can be divided into five categories: one-dimensional (*O*), attractive (*A*), indifferent (*I*), must-be (*M*), and reverse (*R*) [26,50,68]. *One-dimensional attributes* indicate that product attributes are satisfactory and that customer satisfaction is improved. *Attractive attributes* refer to product attributes that customers do not expect the product to have; however, if they exist, consumers are surprised. *Indifferent attributes* refer to the quality characteristics that have no impact on customer satisfaction regardless of their performance. *Must-be attributes* represent the customer's basic demand; when this requirement is satisfied, customers take these attributes for granted. *Reverse attributes*, in contrast to one-dimensional attributes, refer to attributes that, if satisfied, lead to consumer dissatisfaction. Notably, because the purpose of this study is to improve hotel service levels, the reverse attribute is not considered.

However, as the original Kano model was qualitative in nature [71,72], it cannot accurately reflect consumer satisfaction. Accordingly, we draw on the experience of several scholars and adopt an improved Kano model from a quantitative perspective [68]. Bigorra et al. (2019) [12] classified data within the Kano model based on the relative frequency of a given aspect in the overall dataset, product brand advantage, and the proportion of positive and negative mentions of the aspect. Nevertheless, this classification method for determining the importance of product attributes by frequency alone is crude, as more attributes may lead to redundant services [9].

Consequently, this study proposes a hybrid approach that combines joint opinion mining with an improved Kano model while accounting for regional differences to explore changes in consumer demand.

3. Methodology

The research flow is shown in Figure 1, which consists of three phases: data collection, data preprocessing, and data analysis.

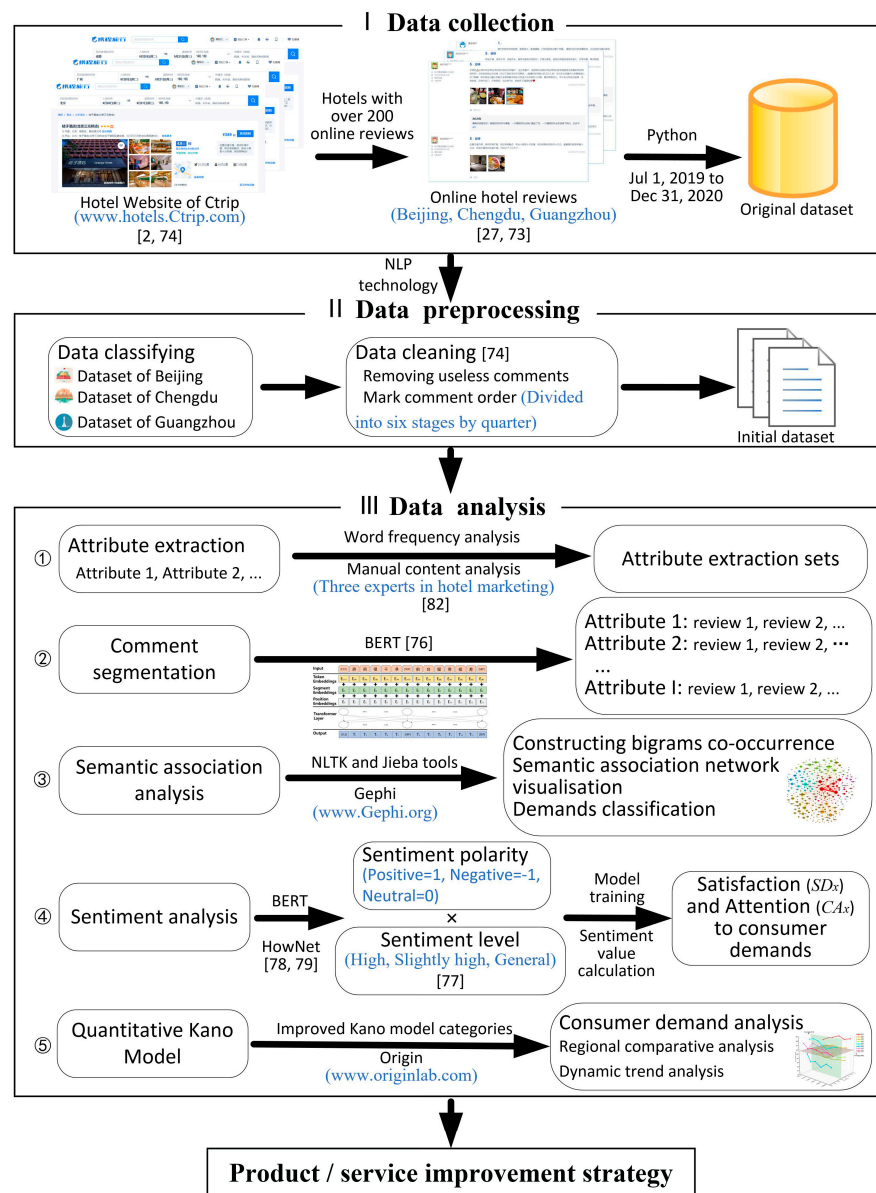


Figure 1. Research flow.

3.1. Data Collection

First, we developed an automatic crawler in Python to collect online hotel reviews from three international tourist cities and regions that may have different preferences in China (Beijing, Chengdu, Guangzhou) [27,73] from Ctrip (<http://www.hotels.ctrip.com> (accessed on 15 March 2021)) [2,74], covering the period from 1 July 2019, to 31 December 2020. Although Booking.com and Tripadvisor.com are major online travel platforms worldwide, their users in China are limited. Ctrip is a leading B2C online hotel platform in China, with its online hotel market consistently ranking first in revenue [2,74]. This time-frame is unique because it includes pre-epidemic (Stages 1 to 2), outbreak (Stages 3 to 4), and normalisation (Stages 5 to 6) periods, during which consumers' decision factors for hotel stays changed significantly [2,66]. To avoid ethical disputes, the researchers collected only online comment texts and corresponding data without collecting identity-related information, as in previous studies such as Zhong et al. (2023) [75]. Next, we referred to the method of Hou et al. (2019) [74] to preprocess the original dataset, including data classifying, data cleaning, and dividing online comments into six stages by quarter. A total of 348,270 valid reviews were collected, among which 84,050, 109,093, and 155,127 were from Beijing, Chengdu, and Guangzhou, respectively.

3.2. Data Analysis

3.2.1. Online Hotel Review Analysis

(1) Hotel attribute extraction. Consumers' related comments on hotels usually revolve around some keywords that correspond to hotel attributes. First, the ranking of hotel attributes is obtained using word frequency analysis. Then, the keywords that match the description of the hotel attributes are labelled, and three experts focusing on hotel marketing are invited to check the screened attribute words and translate Chinese attribute words into English.

(2) Semantic association analysis and demand classification. We use NLTK and Jieba tools to construct semantic association binary phrases for each city and import them into Gephi (www.Gephi.org) to form a visual network diagram. Then, using the network group features in the visual image, we identify the main consumer demands and their key attributes.

(3) Comment segmentation and sentiment analysis. The BERT language model, proposed by Devlin et al. (2018) [76], is built mainly based on the encoder of the transformer architecture based on the self-attention mechanism with word location information to obtain word representations that reflect full learning of the semantics of the context.

In the BERT model, the input is mainly the raw word vector of individual words (also called tokens) in the text. In addition, the input of the BERT model is preceded by the [CLS] flag (see Figure 2, taking the review text '房间很干净, 前台服务极差' as an example), which implicitly represents the semantic features of the whole sentence. The representation of each token obtained after training by the BERT model with CLS is then able to adequately represent the features of each token and sentence. The comment segmentation and sentiment analysis tasks performed in this paper belong to token- and sentence-level tasks, which can be improved using the BERT pretraining model [76].

Notably, sentiment is divided into three categories: positive as 1, negative as -1, and neutral or unmentioned as 0. In this study, each review is identified as $\{r, \text{label}: \{(\text{attribute}: \{(\text{start}, \text{end}): \text{sentiment}\})\}\}$, where r is a single comment, label is the attribute and sentiment label contained in that comment, attribute is the hotel attribute, (start, end) identifies the position of that attribute in that comment, and sentiment is the sentiment classification of the comment on that attribute. After using the comment segmentation to obtain the location identification, sentiment classification can be performed by fine-tuning the BERT model based on the labelled data to obtain the sentiment tendency of each comment containing the attribute. In addition, the degree word is also a crucial key element of the review text, a term used to describe the customer's sentiment level that can be classified into different levels according to its meaning [77]. Therefore, we apply the degree adverbs

by the HowNet lexicon [78,79] as a dictionary resource to calculate the sentiment tendency values of attribute words in a more fine-grained way.

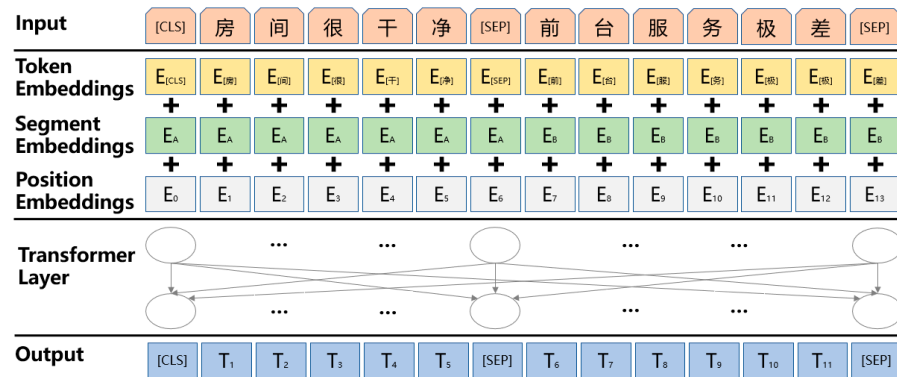


Figure 2. Input sequence and vector representation.

3.2.2. Consumer Demand Classification

To make consumer demand classification more quantitative, we assume that N represents the set of hotel attributes, namely, $N = \{1, 2, \dots, n\}$; R indicates the set of reviews, that is, $R = \{1, 2, \dots, r\}$. S_{xi} represents the sentiment tendency of the i th attribute in the hotel review of the x th demand, while R_{xi} describes the number of comments for the i th attribute in the x th demand, where $x \in [1, 2, \dots, 8]$, $i \in N$. By averaging the sentiment tendencies of each hotel attribute, the average consumer satisfaction for that attribute is obtained, and the equation is as follows:

$$SD_x = \frac{1}{R_{xi}} \sum_j S_{xij} \quad (1)$$

where S_{xij} denotes the probability that the j th review in the x th demand has a sentiment tendency toward the i th hotel attribute, $S_{xij} \in [-1, 1]$, $j = 1, \dots, R_{xi}$. The overall satisfaction SD_x of consumer demand x can be obtained by calculating the sum of the corresponding attribute satisfaction in that demand. A higher SD_x indicates high overall consumer satisfaction with hotel demand x .

The number of comments or the frequency of mentioning attributes reflects the level of consumer attention to key attributes. Thus, we build an indicator CA_x to describe the attention level of consumer demand. CA_x represents the sum of the attention levels for the hotel attributes in the x th demand. Among them, CA_{xi} represents the average attention level of the i th hotel attribute in the x th demand among consumers and represents the demand level of hotel attribute i in the group, which can be defined as follows:

$$CA_x = \sum CA_{xi} = \sum \frac{R_{xi}}{R} \quad (2)$$

When CA_x is close to 1, the x th demand receives greater overall consumer attention. When CA_x is close to 0, the overall consumer attention to the x th demand is low.

To better classify consumer demand through the Kano model, we draw on the experience of Chen et al. (2022) [80] and propose an optimisation model for the Kano classification threshold as follows:

$$c(D_x) = \begin{cases} \text{one-dimensional, if } SD_x \geq \overline{SD}, CA_x \geq \overline{CA} \\ \text{attractive, if } SD_x \geq \overline{SD}, CA_x < \overline{CA} \\ \text{indifferent, if } SD_x < \overline{SD}, CA_x < \overline{CA} \\ \text{must-be, if } SD_x < \overline{SD}, CA_x \geq \overline{CA} \end{cases} \quad (3)$$

where $c(D_x)$ represents one of the four demands classified by Kano for the x th demand, and $\overline{SD}$ and $\overline{CA}$ represent the mean satisfaction and attention of demands at all stages, respectively.

4. Results

4.1. Attribute Extraction

Through the Jieba Chinese word segmentation system in Python and the NLTK tool, each online hotel review is processed by word separation and lexical annotation for word and word frequency statistics. To make the data more rigorous, we calculate the threshold of high-frequency words in each stage of the three cities based on the demarcation method of high-frequency words and low-frequency words proposed by Donohue (1973) [81]. Since non-high-frequency words may also affect results [74], this study appropriately extends the high-frequency words by adding 50 keywords for each stage to be analysed and calculating the frequency of the keywords. From stage 1 to stage 6, the thresholds for Beijing are 370, 321, 150, 131, 218, and 270, respectively. The thresholds for Chengdu are 535, 337, 175, 217, 324, and 323, respectively. The thresholds for Guangzhou are 417, 387, 228, 289, 385, and 357, respectively. Our results show that Room is the most mentioned keyword by hotel users in each city. In Beijing, Clean, Breakfast, and Front Desk are the most frequently mentioned keywords. In Chengdu, users may care more about Breakfast, Clean, and Front Desk, so these rank among the top two and top three keywords in different stages. In Guangzhou, Clean and Front Desk are basically second and third in order, respectively. Some of the top attributes also rank slightly differently in different stages.

4.2. Binary Semantic and Visualisation Analysis

4.2.1. Constructing Bigram Co-Occurrence

As shown in Table 1, the binary phrases constructed by the cities are very similar; Room-Clean, Clean-Neat, Traffic-Convenient, Room-Facilities, Front Desk-Enthusiasm, and other binary phrases are most mentioned by consumers, indicating that room hygiene, traffic convenience, front desk service, etc., are the primary demands of consumers. To some extent, this finding is consistent with the previous findings.

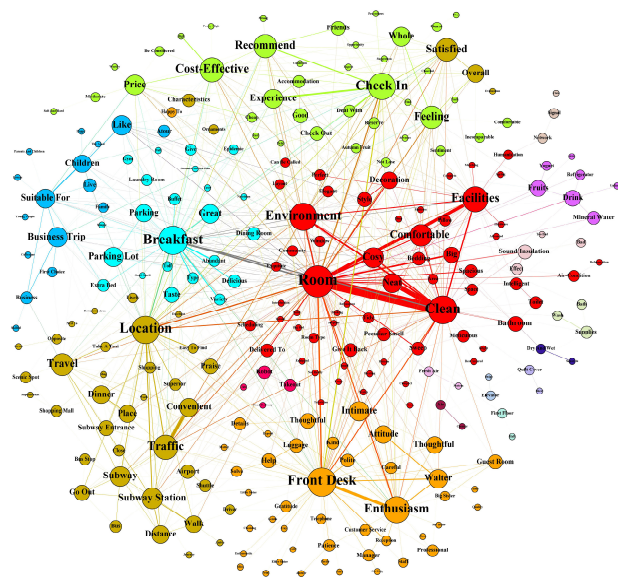
Table 1. Binary phrases in each city.

Beijing		Chengdu		Guangzhou	
Source-Target	W.	Source-Target	W.	Source-Target	W.
Room-Clean	8839	Room-Clean	10,078	Room-Clean	15,557
Clean-Neat	4513	Clean-Neat	6007	Clean-Neat	9653
Traffic-Convenient	3130	Front Desk-Enthusiasm	3870	Traffic-Convenient	5730
Room-Facilities	2901	Traffic-Convenient	3793	Room-Facilities	4917
Front Desk-Enthusiasm	2731	Room-Facilities	3691	Front Desk-Enthusiasm	4055
...	...	...	...	...	...

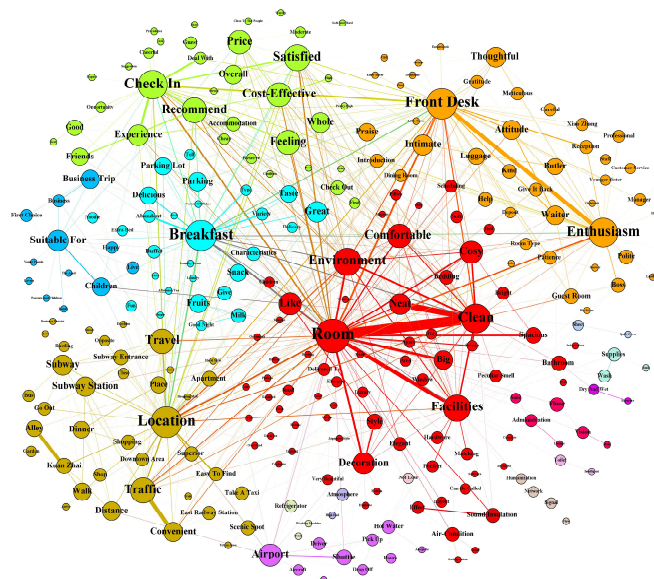
Note: W. is an abbreviation for Weight.

4.2.2. Semantic Association Network Visualisation

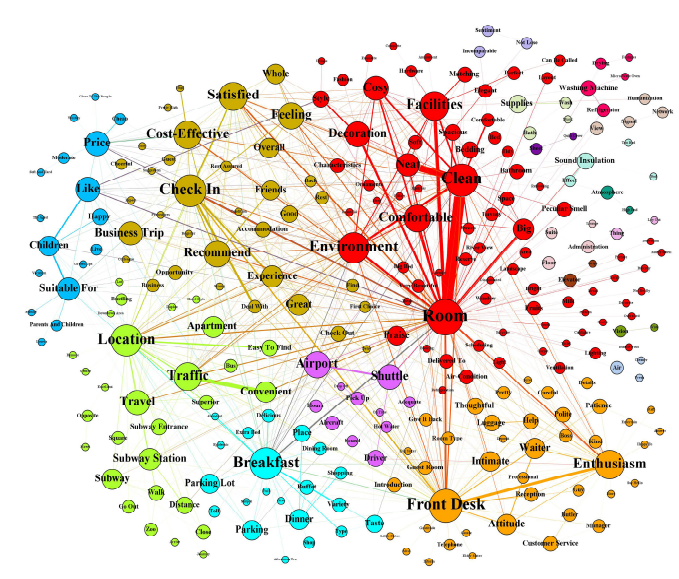
We selected the first 1000 binary phrases from each city and imported them into Gephi 0.9.2 for semantic association analysis. In the graph, each node represents the corresponding keyword/attribute. The larger the node is, the greater the weight of the attribute in consumer demand. The connecting line indicates the correlation between the nodes, and a thicker connecting line indicates a greater correlation between them. In this study, drawing on Yu et al. (2023) [2], the nodes of each community are coloured red, orange, gold, green, yellow, and so on. The higher the colour is, the greater the proportion of the whole network is, reflecting the priority of hotel consumers' demands, as shown in Figure 3.



(a) Beijing



(b) Chengdu



(c) Guangzhou

Figure 3. Network visualisation for each city.

4.2.3. Demand Classification

Based on the network visualisation analysis in the previous section, we adopt a manual content analysis method (MCA) [82] to classify consumer demands and key attributes, while increasing the rigour and flexibility of the study. To ensure the validity and reliability of the categorisation, four PhD student assistants were invited to participate in the MCA process. The patients were divided into two groups and worked independently and simultaneously without any discussion. If there was a controversial word in the group, it was marked as “uncertain” and then discussed with the rest at the end. Following the categorisation process, the final demand categorisation was verified by two experts. Table 2 shows the main demands in each city (to save space, only the top 5 key attributes are shown for each demand). Clearly, Environment & Facilities, and Location & Traffic are the most important demands for consumers. However, the level of satisfaction and attention given to each demand need to be further analysed.

Table 2. Consumer demand classification.

No. of Demand	Beijing		Chengdu		Guangzhou	
	Consumer Demand	Key Attributes	Consumer Demand	Key Attributes	Consumer Demand	Key Attributes
D1	Environment & Facilities	Room, Environment, Facilities, Decoration, Style...	Environment & Facilities	Room, Clean, Environment, Facilities, Decoration...	Environment & Facilities	Room, Clean, Environment, Facilities, Decoration...
D2	Front desk service	Front Desk, Enthusiasm, Waiter, Attitude, Thoughtful...	Front desk service	Front Desk, Enthusiasm, Waiter, Attitude, Thoughtful...	Front desk service	Front Desk, Enthusiasm, Waiter, Attitude, Thoughtful...
D3	Location & Traffic	Location, Traffic, Travel, Subway Station, Convenient...	Location & Traffic	Location, Traffic, Travel, Subway Station, Convenient...	Check in & Cost-effective	Check In, Cost-Effective, Feeling, Satisfied, Whole...
D4	Check in & Cost-effective	Check In, Cost-Effective, Feeling, Price, Whole...	Check in & Cost-effective	Check In, Cost-Effective, Feeling, Price, Satisfied...	Location & Traffic	Location, Traffic, Travel, Apartment, Subway Station...
D5	Breakfast & Parking	Breakfast, Parking Lot, Parking, Taste, Buffet...	Breakfast & Parking	Breakfast, Parking Lot, Parking, Taste, Buffet...	Breakfast & Parking	Breakfast, Parking Lot, Parking, Dinner, Taste...
D6	Travel type	Children, Like, Business Trip, Live...	Travel type	Children, Business Trip, Live, Business...	Price & Children	Price, Like, Children, Happy, Cheap...
D7	Drink	Drink, Fruits, Mineral Water, Yogurt...	Shuttle	Airport, Shuttle, Driver, Pick Up, Drop off...	Shuttle	Airport, Shuttle, Driver, Pick Up, Aircraft...
D8	Other	Satisfied, Overall, Network, Sound Insulation, Effect...	Other	Supplies, Sheet, Floor, Vision, Dry And Wet...	Other	Supplies, Wash, Bath, Sheet, Washing Machine...

4.3. Comment Segmentation and Sentiment Analysis

In this paper, 10,000, 12,000, and 18,000 review data points are randomly selected from Beijing, Chengdu, and Guangzhou, respectively, and the aggregated review data are randomly divided into training (Train) and validation (Dev) sets at a ratio of 8:2 for single-sentence classification training and sentiment classification training on hotel attributes [76,79]. The training results demonstrate that the pretraining accuracy is 97.98%, the recall is 97.95%, and the F1 value is 97.95%. Therefore, the pretrained BERT model is

more effective than the other models and can be used for sentiment analysis of hotel attributes.

4.4. Dynamic Analysis of Consumer Demand

Based on the above formula, we calculate the satisfaction and attention level of consumer demand at each stage. The 3D drawing function in Origin 2022 (www.originlab.com) was used to develop a trend graph of dynamic Kano demand classification for each city, as shown in Figure 4. In this case, the demands in the figure are still divided according to the colour order of the semantic association network visualisation, with the cross section representing the average satisfaction (green, with 90% transparency) and the longitudinal cross section representing the average attention (orange, with 90% transparency). Notably, according to formula (3), the plane formed by satisfaction and attention is divided into four demand quadrants in the cross-sectional and longitudinal sections. The first quadrant represents *O* (One-dimensional), the second quadrant is *A* (Attractive), the third quadrant represents *I* (Indifferent), and the fourth quadrant represents *M* (Must-be).

As Figure 4a illustrates, in the first stage *O* includes **D1** (Environment & Facilities); *A* includes **D5** (Breakfast & Parking), **D7** (Drink), and **D8** (Other); *I* includes **D6** (Travel type); *M* includes **D2** (Front desk service), **D3** (Location & Traffic), and **D4** (Check in & Cost-effective). Subsequently, **D1** increased in satisfaction and attention in *O*, indicating that consumers' demands were better satisfied in **D1** but decreased in Stage 5. Interestingly, **D2** started to become an *O* in Stage 2 with a similar change trend as **D1**. The more obvious changes in *A* are **D5** and **D7**, the former slightly increasing (Stage 2), then decreasing (Stage 3–4), and then increasing (Stage 5–6), and the latter decreasing (Stage 2), then increasing (Stage 3), and then decreasing (Stage 4–6). **D8**, on the other hand, has an insignificant trend and is basically at the junction between *A* and *I*. Among *I*, **D6** is always in this demand classification, but its satisfaction fluctuates more, such as plummeting in Stage 2 and then showing an overall decreasing trend. Although this demand is volatile, it does not have much material impact on consumer demand. Among the *M*, both **D3** and **D4** have some fluctuations, the former mainly in the sudden drop (Stage 2–4) and rebound (Stage 5–6) of the attention, while the latter's satisfaction and attention have a small increase in Stage 4, but its satisfaction drops back to the level of 0.4 or below in Stage 5.

In Figure 4b, in Stage 1, **D2** (Front desk service) is an *O*, **D5** (Breakfast & Parking) and **D7** (Shuttle) are categorised as *A*, **D6** (Travel type) and **D8** (Other) are *I*, and **D1** (Environment & Facilities), **D3** (Location & Traffic), and **D4** (Check in & Cost-effective) are classified as *M*. Among the *O*, **D2**'s satisfaction increases (Stage 2–4) and then decreases (Stage 5–6), while its attention increases abruptly (Stage 2), then decreases (Stage 3), and then increases slowly (Stage 4–6). Among *A*, **D5**'s attention fluctuates more, mainly showing a sudden decrease in Stage 3 and then a slow increase in Stage 5–6. In addition, **D7** has no significant fluctuation of change. In *I*, **D6** and **D8** have a more obvious change trend in satisfaction, with **D6** decreasing (Stage 2–4), then increasing (Stage 5), and decreasing (Stage 6), while **D8**'s trend is the opposite of **D6**. Among *M*, **D1** is always at the boundary between *O* and *M*, but its attention drops sharply in Stage 5; **D3**'s satisfaction gradually increases, but its attention gradually decreases; and **D4**'s satisfaction does not fluctuate much, but its attention slowly increases (Stage 2–4) and then slightly decreases (Stage 5–6).

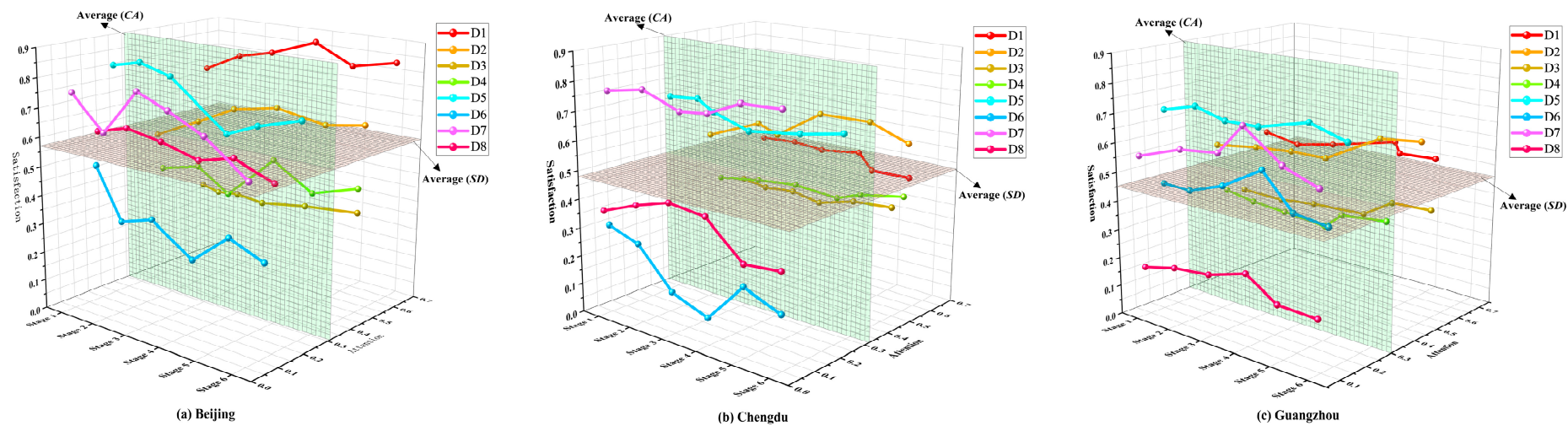


Figure 4. Dynamic consumer demand changes for Kano categorisation.

In Figure 4c, in Stage 1, *O* includes **D1** (Environment & Facilities) and **D2** (Front desk service), *A* includes **D5** (Breakfast & Parking) and **D7** (Shuttle), *I* includes **D6** (Price & Children) and **D8** (Other), and *M* includes **D3** (Check in & Cost-effective) and **D4** (Location & Traffic). Among the *O*, the satisfaction of **D1** does not change significantly, but its attention shows an increase (Stage 2–4) and then a decrease (Stage 5–6), while the satisfaction and attention of **D2** both increase slowly, especially after Stage 4. Among *A*, **D5**'s satisfaction increases and then decreases in Stage 5, while its attention gradually increases in Stage 5–6. Interestingly, **D6** oscillates between *A* and *I* (e.g., Stage 3–5), with the greatest changes mainly in satisfaction. **D7** also fluctuates somewhat in satisfaction and attention but remains in *A*. Among *I*, **D8**'s satisfaction increases (Stage 2–4) and then decreases (Stage 5–6). In *M*, **D3**'s satisfaction and attention both increase slowly after Stage 4, and **D4**'s satisfaction and attention both fluctuate more, such as satisfaction dropping to 0.3 in Stage 4 and rising to 0.4 in Stage 5, and its attention drops from 0.4 to close to 0.3 in Stage 5.

In addition, there are differences in demand between different cities. In *O*, Beijing always includes **D1**, Chengdu always includes **D2**, and Guangzhou always includes **D1** and **D2**. In terms of *A*, the three cities always include **D5** and **D7**. It is worth noting that **D7** in Chengdu and Guangzhou is a Shuttle. In *I*, Beijing always includes **D6**, Chengdu always includes **D6** and **D8**, and Guangzhou always includes **D8**. In *M*, all three cities always include **D3** and **D4**.

5. Discussion of Findings

Firstly, we found differences in the key attributes mentioned by consumers in different cities. Room is the attribute most mentioned in each stage in all three cities, similar to Yu et al. (2023) [2]. However, unlike previous research findings [83,84], in each stage, Beijing consumers mentioned Clean, Breakfast, and Front Desk more often; Chengdu consumers paid more attention to Breakfast, Clean, and Front Desk; and Guangzhou consumers mentioned Clean and Front Desk more. Basically, these attributes rank among the top rankings. In addition, consumers in Beijing and Chengdu are more concerned about Location & Traffic, while consumers in Guangzhou are more concerned about the demands Check in & Cost-effective. This may be related to the characteristics of the destination cities, as Beijing and Guangzhou are high-intensity and fast-paced areas where the majority of hotel guests are on business trips, and these guests are more focused on service and comfort. In contrast, in Chengdu, which is characterised by “leisure capital” [85], most hotel guests are on leisure trips and are more concerned with a restful experience.

Secondly, the satisfaction and attention of consumer demands fluctuate in different stages. Compared to previous studies [66], this study revealed that consumer satisfaction and attention did not effectively recover after experiencing major events (e.g., COVID-19). In Beijing, **D5** has the highest satisfaction in the first two stages, while in Stage 3–6, **D1** does. **D3** has the lowest satisfaction in Stage 1–3, while **D6** is the demand with the lowest satisfaction in Stage 4–6. **D1** and **D7** are the demands with the highest and lowest attention levels in each stage, respectively. In Chengdu, **D7** and **D6** have the highest and lowest satisfaction demands, respectively, in each stage, with **D1** having the highest level of attention and **D6** or **D8** having the lowest. In Guangzhou, **D5** always has the highest satisfaction (except for Stage 4, which is **D7**), and the lowest satisfaction is **D8**. **D1** is the demand with the highest level of attention, and the lowest level of attention is **D7** or **D8**. This may be because there are more hotels in Beijing and Guangzhou that offer convenient options for breakfast and parking but that hotels in Chengdu provide better pick-up and shuttle services.

Thirdly, consumer demand will change over time. Previous scholars often considered consumer demand from a static perspective [86], ignoring the fact that it is a dynamic concept. In Beijing, in the first stage, *O* includes **D1**, *A* includes **D5**, **D7**, and **D8**, *I* includes **D6**, and *M* includes **D2**. The demands with significant changes include **D2**, **D5**, **D7**, and **D6**, where **D2** changes from *M* to *O*. In Chengdu, in Stage 1, **D2** is classified as *O*, **D5** and **D7** are classified as *A*, **D6** and **D8** are classified as *I*, and **D1**, **D3**, and **D4** are classified as *M*.

D2, **D6**, and **D8** show a clear change trend, with **D2** mainly showing significant fluctuations in attention and **D6** and **D8** showing a significant opposite change in satisfaction. In Guangzhou, in the first stage, *O* includes **D1** and **D2**, *A* includes **D5** and **D7**, *I* includes **D6** and **D8**, and *M* includes **D3** and **D4**. Among them, **D4**, **D6**, and **D7** display more obvious changes. **D4**'s satisfaction and attention fluctuate significantly after Stage 4, while **D6** and **D7**'s fluctuations are mainly reflected in satisfaction. This may be due to differences in the attributes of different stages [24,25] or destination cities [73].

6. Research Implications

6.1. Theoretical Implications

In this paper, we identify the differences in consumer demand in a more nuanced way via comparative analysis of hotels in different cities. Most of those previous studies focused only on a single city or considered hotel reviews of multiple cities as a whole [2], ignoring the possible differences in consumer demand among hotels in different cities [27].

Therefore, the current study provides a new way to improve the accuracy of consumer demand mining, compensating for the limitations of analysing online hotel reviews as static data from a dynamic evolutionary perspective. This method tracks the changing trends in consumer demand in a more fine-grained way [60]. We collect degree words and negation words as candidates for sentiment analysis and quantify the degree of affective polarity. Thus, this research addresses the deep integration of attribute terms and contextual semantics with a new contextual customer sentiment generation method. Accordingly, the results of the above analysis have improved the accuracy and applicability of the customer demand measurement model from a dynamic perspective.

This study employed a hybrid approach to mine consumer demand. Previously, questionnaires and interviews have been used to understand consumer demands [20,80]; these methods are time consuming and inaccurate [61,87]. In contrast, we obtain numerous valid online hotel reviews using Python, and thereby avoid the "laboratory effect" [88]. In addition, our research integrates opinion mining, the BERT model, and the improved Kano model, providing a new model for mining consumer demand. For example, the visual characteristics of using 3D Kano model classification can help us quickly understand and identify trends in consumer demand.

6.2. Practical Implications

We provide a novel framework offering insights for hoteliers to effectively mine consumers' demands from online reviews. This study integrates NLP technology (e.g., opinion mining, BERT model), Gephi, Origin, and the Kano model. Hotel managers can thereby identify consumers' demands in greater depth using online reviews and determine the attributes that are likely to improve customer satisfaction [14]. In the era of big data inflation, we suggest that managers should not be limited to traditional methods of demand identification (e.g., questionnaires and interviews) but should use updated methods to understand consumer demands.

Our research can also help companies track changing consumer demands in real time. The time-tagged nature of online reviews allows managers to rely on large amounts of data to gather valuable, real-time insights. For example, hoteliers can adopt dynamic pricing, based on the importance of attributes in different stages [89], to meet the dynamic demands of consumers and thus increase hotel revenue. Additionally, practitioners can perform timely analysis of customer demands via online reviews and provide much-needed support for their product development efforts. For example, hotel managers in Beijing can continue to maintain the attractiveness of their Breakfast & Parking services. Chengdu hotel practitioners need to focus on increasing consumers' attention to the Environment & Facilities and Location & Traffic of rooms. Managers in Guangzhou should increase consumers' satisfaction and attention toward their Price & Children efforts.

The results suggest that companies should optimise their products or services for important consumer demands with limited resources. Improving service quality can ef-

fectively improve hotel operational performance [33]. To reduce costs and improve consumer experiences, product improvement needs to account for consumers' emotions regarding the focal product and categorise and rank its attributes or consumers' demands. In general, managers should provide services in the order of "must-be demand > one-dimensional demand > attractive demand" and avoid providing too many resources in terms of indifferent and reverse demand [9]. For example, hotel practitioners in various cities should meet the demands of consumers in terms of Location & Traffic and Check in & Cost-effective, which are consumers' must-be demands. Regarding consumers' one-dimensional demands (e.g., Environment & Facilities), managers should quickly develop optimised responses. For attractive demands (e.g., Breakfast & Parking), hotel practitioners should seize the above result and use the attractive demand as the selling point of their hotel to attract more customers. In addition, the three cities in this article are representative cities in different regions of China, and the research results can also serve as a reference for hotel managers in surrounding cities to improve service quality.

6.3. Limitations and Future Research

Although the research in this paper has several theoretical and practical implications, it has several limitations. Firstly, our data came from only one online hotel platform, which may not provide complete information about customer opinions [74], resulting in bias in the results. There is a need to expand the data sources in the future, such as Ctrip vs. TripAdvisor, to enhance the universality of the research results. Secondly, the differences between different types of hotels (e.g., budget and luxury) were not considered [68]. For instance, each hotel should be segmented separately as a product and more finely grained to explore its unique attributes or future performance. Thirdly, there are slices of implicit attributes or demands in some comments (e.g., photo and video reviews), which are still difficult to accurately identify using current methods. Therefore, future research can utilise more advanced analysis methods (e.g., convolutional neural networks).

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