Modeling customer satisfaction and revisit intention from online restaurant reviews: an attribute-level analysis

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Abstract
Purpose – The purpose of this paper is to detect predefined service attributes and their sentiments from online restaurant reviews, and then to measure the effects of customer sentiments toward service attributes on customer satisfaction (CS) and revisit intention (RVI) simultaneously.
Design/methodology/approach – This study proposed a supervised framework to model CS and RVI simultaneously from restaurant reviews. Specifically, the authors detected the predefined service dimensions from online reviews based on random forest. Then, the sentiment polarities of the reviews toward each predefined dimension were identified using light-gradient boosting machine (LightGBM). Finally, the effects of attribute-specific sentiments on CS and RVI were evaluated by a bagged neural network-based model. The proposed framework was evaluated by 305,000 restaurant comments collected from DianPing.com, a Yelp-like website in China.
Findings – The authors obtained a hierarchical importance order of the investigated service themes (i.e., location, service, environment, price, and food). The authors found that food played the most important role in affecting both CS and RVI. The most salient attribute with respect to each service theme was also identified.
Originality/value – Unlike prior work relying on the data collected from surveys, this study is among the first to model the relationship among service attributes, CS, and RVI simultaneously from real-world data. The authors established a hierarchical structure of eighteen attributes within five service themes and estimated their effects on both CS and RVI, which will broaden our understanding of customer perception and behavioral intention during service consumption.

Keywords Online reviews, Text mining, Service attributes, Customer satisfaction, Revisit intention

Paper type Research paper

1. Introduction
In the context of hospitality and service, unveiling the impacts of service quality attributes on customer satisfaction (CS) and revisit intention (RVI) plays an important role in developing management insight and improving service delivery, especially in the restaurant sector (Mejia et al., 2021). As such, it has drawn aggressive attention from researchers in this field. However, there exist challenges in establishing a clear relationship among these variables about consumer behavior and restaurant performance (Vencovský, 2020). In comparison with product quality, service quality is hard to evaluate due to its intrinsic nature such as intangibility and variability (Christian, 1984). To tackle this challenge, two survey approaches, including questionnaires and interviews, are usually applied to measure service quality from the viewpoint of customer experience (Berry et al., 1998; Parasuraman et al., 1985). Although the measurement scales used in the surveys such as DINESERV are well-established, the approaches have twofold shortcomings accompanied by their prevalent applications. First of all, it is challenging to
provide generalized and scalable measures because of the heterogeneous consumer preferences and time-varying restaurant operations (Mejia et al., 2021). Second, the costs of conducting surveys are huge in both time and labor. Therefore, more academic attempts need to be made on service evaluation via exploring other alternative channels.

With the advent of digital platforms, consumer-generated content presented on online review websites opens up new avenues for measuring customer experience and service quality (Chen et al., 2020; Schuckert et al., 2015). Third-party platforms like Yelp and DianPing allow consumers to post online reviews about post-purchase feedback, which in turn facilitates prospective consumers to make informed decisions. Prior work has highlighted the value of online reviews in many research fields such as product design (Bi et al., 2019; Qi et al., 2016), market segmentation (Ahani et al., 2019) and trust perception (Cheng et al., 2019). Moreover, a substantial body of literature has attempted to mine service dimensions, CS and RVI from service-related reviews, particularly in the hotel and airline industries (Bi et al., 2020; Lucini et al., 2020; Luo and Tang, 2019; Park, 2019; Park et al., 2020a, 2020b; Zhao et al., 2015, 2019). In contrast to surveys, online review data not only contain realistic, spontaneous and comprehensive information regarding consumer experience (Vidal et al., 2016), but also can provide restaurant managers with operational advantages derived from its large volume, easy availability and low cost (Tian et al., 2021). In this regard, we argue that online reviews can serve as an alternative potential information source to effectively understand service attributes, customer experience and behavioral intention in the restaurant industry.

We conducted a comprehensive review of related publications and found that limited and yet fast-expanding studies have used online review data to analyze dining experience in a more complete and up-to-date manner (Gan et al., 2017; Jia, 2020; Kim et al., 2020; Liu et al., 2020; Mejia et al., 2021; Nakayama and Wan, 2018; Tian et al., 2021; Vu et al., 2019; Yan et al., 2015; Zhu et al., 2019). To the best of our knowledge, two research gaps are existing in the relatively scarce literature. Theoretically, the majority of these studies focused on exploring the effect of restaurant service attributes on overall CS. Despite the relevance of retaining existing customers to the restaurant performance (Kim et al., 2009), few attempts have been made to capture RVI from online restaurant reviews. Methodologically, amid the wealthy and diversified information of online reviews, prior research typically used only review metadata such as numerical ratings to explore food-related sentiments (Liu et al., 2020; Yan et al., 2015). Moreover, although some extant studies have concentrated on the textual review content, most of them adopted techniques such as content analysis and topic model to uncover the service dimensions hidden in the texts (Mejia et al., 2021; Tian et al., 2021). These used methods, which can be categorized into unsupervised ways, might be not applicable in supervised scenarios where a set of predefined service dimensions are given by restaurateurs or platforms.

The current research was therefore conducted to overcome the two limitations by proposing a supervised framework to model CS and RVI simultaneously from textual reviews. Specifically, our research was motivated by the following facts. First, prior research usually used online customer rating scores to represent CS. However, it was difficult to find a similar proxy for RVI. Textual reviews had the potential to represent the two variables with accurate values. Moreover, few studies focused on CS and RVI simultaneously, and it was still unclear about the difference between the impacts of service quality on the two important service outcome variables, which might be valuable for the service operation strategies. Finally, most of the previous work used unsupervised methods to mine service attributes from reviews. Given a certain service attributed provided by platforms or restaurant managers, previous methods failed to measure its impact on CS and were not suitable for this situation. In sum, this study aims to fulfill the following research objectives:

**ROI.** To detect predefined service dimensions and their sentiments from online restaurant reviews based on supervised learning.
RO2. To measure the effects of customer sentiments toward attributes on CS and RVI and identify whether there is any inconsistency between these effects.

2. Literature review

2.1 Online restaurant reviews

In recent years, online customer reviews (OCRs) have drawn massive attention from firm managers and allowed them to harness these new data sources for decision support (Dellarocas et al., 2007). With the growing popularity of OCR, it has become an important information source in many fields, such as marketing (Li et al., 2022), tourism management (Qin et al., 2022) and healthcare (Placona and Rathert, 2022). Online reviews allow product or service providers to utilize this kind of collective wisdom to develop or update their products or services.

With the advent of platforms like Yelp and DianPing, online restaurant reviews, which reflect spontaneous customer dining experience, have become a well-established information source for restaurant service evaluation (Vencovsky, 2020; Vidal et al., 2016). Specifically, potential customers hinge on online reviews to make patronage decisions while restaurant managers garner customer feedbacks to formulate service improvement strategies. As such, online restaurant reviews are influential on bilateral service-centric behaviors, both online and offline. Further, research evidence exists to support the significance of customer-generated content in correlation with restaurant performance indicators, such as sales (Lu et al., 2013), survival (Mejia et al., 2021), online popularity (Zhang et al., 2010), overall CS (Gan et al., 2017) and RVI (Yan et al., 2015).

Despite the more promising prospect indicated by textual content (Wu et al., 2015; Xu, 2019), most of the existing studies use one-dimensional numerical data to represent customer opinions (Yan et al., 2015; Zhu et al., 2019). However, to better understand CS and RVI, researchers and practitioners should evaluate the dining experience in a multi-faceted way (Bi et al., 2020; Chen and Chen, 2015). Therefore, a few recent studies in the restaurant literature attempt to exploit textual review content. For instance, Mejia et al. (2021) first used nonnegative matrix factorization (NMF) to extract service quality themes from online review text. Various experiments were then carried out to test the identified dimensions. Finally, the correlation between these dimensions and restaurant survival was revealed through an empirical study. Other researchers often utilized content analysis method to obtain customer perception from restaurant reviews (Kim et al., 2020; Pantelidis, 2010; Tian et al., 2021). However, these unsupervised methodologies are not applicable in supervised problem settings where a set of predefined service dimensions are provided (Duan et al., 2016). As a result, it motivates us to construct a supervised framework to detect given service attributes from online reviews in this paper.

2.2 Dining experience, customer satisfaction and revisit intention

Massive literature has been dedicated to understanding the components and consequences of dining experience, due to its crucial role in the restaurant business (Marinkovic et al., 2014). Kleinhans et al. (2016) pointed out that dining experience dimensions have changed over the last few years. The initially popular dining experience factors were tangibles, responsiveness, reliability, assurance and empathy. Nowadys, the majority of these studies have generally reached a consensus on the fact that food, service and price are three essential aspects making up the dining experience (Aryani et al., 2022; Harrington et al., 2012; Hussein, 2018; Namkung and Jang, 2007; Pantelidis, 2010). However, the identification of other service themes still deserves comprehensive efforts. For instance, Oh and Kim (2020) implied that the quality dimensions of traditional restaurants may not accurately represent the factual dimensions, which needed to be updated accordingly. As such, Longart et al. (2018) presented a new model comprising seven categories of restaurant attributes based on a systematic survey of related work. Their final classification results consisted of food and drink, ambiance and atmosphere, facilities, service,
location, image and price. By combining physical and mental environment, ambiance and facilities were reduced to one dimension, i.e. environment category in several studies (Hyun, 2010; Zhang et al., 2014). Further, research on the definition and measurement of location is relatively scarce (Wong and Zhao, 2016). Moreover, considerable literature on restaurant attributes notwithstanding, the hierarchical order of their importance is inconclusive (Gan et al., 2017). This research gap might be caused by the difference in used methodologies or investigated contexts and should be filled with a more in-depth analysis.

CS refers to an overall evaluation based on the comparison between perceived performance and pre-purchase expectations, serving as a fundamental predictor of restaurant performance and consumer behavior (Fornell, 1992; Namkung and Jang, 2007). With regard to the drivers of CS, prior work has provided extensive evidence for the significance of dining experience attributes (June and Smith, 1987; Kim et al., 2009; Marinkovic et al., 2014), especially in the contexts of full-service, fast food or chain restaurants (Chun and Nyam-Ochir, 2020; Hyun, 2010; Ryu and Han, 2010; Sabir et al., 2014; Weiss et al., 2005). For example, Chun and Nyam-Ochir (2020) evaluated factors including food, atmosphere, service, and price in both local and global fast-food restaurants using the DINESERV scale. Their results showed that all of the four investigated themes had a positive correlation with CS. Choi et al. (2022) examined the effects of six dimensions including food quality, service quality, atmosphere, convenience, price and vegetarian menu options, on the CS of vegetarian customers and found that only price and vegetarian menu options had significant positive effects on vegetarian customers’ satisfaction. Kim et al. (2022) investigated the impact of customers’ service perception in online reviews on CS and revealed the importance of price and location in the restaurant industry. In the same vein as the restaurant type, the moderating role of cultural origin and generation gap was also uncovered by extant literature (Harrington et al., 2012; Jia, 2020; Nakayama and Wan, 2018).

In terms of the consequences of CS, RVI has been regarded as merely an extension of CS in previous studies (Um et al., 2006). However, with behavioral components omitted, it will be difficult to understand the relatively high importance of RVI in restaurant operations (Mittal et al., 1998; Yan et al., 2015). Some researchers argued that RVI, taking into account its role in repeat decisions, is an indispensable dependent variable for investigations on service delivery and market insights (Hume and Mort, 2010). Therefore, a few prior studies paid attention to the direct effect of attribute-level performance on RVI (Mittal et al., 1998; Meng and Choi, 2018; Richardson et al., 2019). For instance, Richardson et al. (2019) examined the impact of dining experience attributes on RVI to quick-service restaurants in the USA. The analyzed attributes including food, service and environment were found to be influential factors in customers’ intent to revisit and recommend the restaurants. Polas et al. (2022) examined the direct impact of service quality, physical environment and price perception on customers’ RVI, and the results demonstrated a positive relationship among the investigated variables based on the interview of 317 Generation Z respondents selected from 10 halal restaurants in Bangladesh. Sirimongkol (2022) found the relationship between restaurant service quality and RVI and the moderating effect of trust on this relationship in the background of COVID-19.

Most previous research examined the relationship among dining experience, CS and RVI using the data collected from surveys. However, it is difficult to extract complete customer perception merely through the questions in the employed questionnaires. Despite the increasing number of studies modeling CS from review data, research capturing RVI from restaurant reviews is scarce. Building on this work, we focused on extracting attribute-level performance, CS, and RVI simultaneously from online review texts. It is a more effective and efficient way to measure the complex dining experience. Moreover, we also estimated the impact of attribute performance on CS and RVI based on the extracted outcomes.
3. Methodology

Figure 1 illustrates the proposed research framework, which can be divided into three parts: (1) detecting predefined dimensions from online reviews; (2) identifying customers’ opinions toward each predefined dimension from online reviews; (3) estimating the effects of customer sentiments toward each attribute on CS and RVI. A detailed description of each part will be given in Section 3.2, 3.3, and 3.4, respectively.

3.1 Data collection and preprocessing

The data set used in this work was directly provided by Dianping.com, the biggest third-party review platform in China. The original data set consisted of 105,000 reviews which were labeled under 20 predefined dimensions and 200,000 unlabeled restaurant reviews. Except for two dependent variables, CS and RVI, the predefined service dimensions also included 18 restaurant attributes belonging to five service themes as shown in Table 1. Table 2 displays the structure of the labeled data subset in which the sentiment polarity of one dimension in a review can be positive, neutral or negative. Further, “Not mentioned” indicates that there was no content regarding the specific dimension in the review.

We performed several text preprocessing steps before the modeling procedure. First, we translated traditional Chinese into simplified Chinese to maintain the review text in a unified format. Second, we conducted sentence and word segmentation using Jieba, a popular analysis tool dedicated to Chinese language processing. Moreover, we combined the restaurant-related cell dictionaries of three prevalent Chinese input methods, Tencent, Sogou and Baidu. Then the enriched lexicon with 159,715 words was employed to improve the precision of word segmentation. Third, after filtering out stop words, we represented the review text based on TF-IDF (Jones, 1973).

3.2 Detecting predefined service dimensions from online reviews

In this part, a mention-oriented classifier for each predefined dimension was built based on online reviews. Let $D = \{d_1, ..., d_j, ..., d_J\}$ denote the set of predefined

![Figure 1. Research framework](source(s): Author’s own creation)
dimensions, where \( d_j \) denotes the \( j \)th dimension. Moreover, the labeled data subset was denoted as \( R = \{ r_1, ..., r_L \}, l = 1, 2, ..., L \) where \( r_l \) denoted the \( l \)th annotated review. The unlabeled review set was also denoted as \( R = \{ r_1, ..., r_u, ..., r_U \}, u = 1, 2, ..., U \) where \( r_u \) denoted the \( u \)th unannotated review. First, if the label of dimension \( d_j \) in review \( r_l \) was positive, neutral or negative, then it was reassigned as “Mentioned”. Second, a binary random forest classifier was trained by the relabeled \( R \) with respect to the \( j \)th dimension. Third, the Gini index was applied to calculate the importance of the word features of the classifier. Then, the words that had top importance were retained after manually filtering because they were highly relevant to the specific dimension. Therefore, the \( j \)th dimension was further represented as \( d_j = \{ word_{j1}, ..., word_{ji}, ..., word_{jI_j} \}, i = 1, 2, ..., I_j, \) where \( word_{ji} \) denoted the \( i \)th important word in the \( j \)th service dimension. Finally, using the obtained words, whether the \( j \)th dimension was mentioned in \( r_u \) was determined by checking whether the review involved the words in \( d_j \). If review \( r_u \) did not include any word in \( d_j \), then the \( j \)th dimension in \( r_u \) was labeled as “Not mentioned”.

3.3 Identifying customers’ opinions toward each predefined dimension from online reviews
In this section, a sentiment-oriented classifier for each service dimension was constructed based on restaurant reviews. First, regarding each review \( r_l \) in \( R \), the sentences that
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structured data of table 3.

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where $r_{jd}$ denoted the $d$th review in $R_j$ and the $b$th one in $R$. $D_j$ represented the size of $R_j$, $a, b, c \in \{1, 2, \ldots, L\}$. In the same vein, the subset of unlabeled reviews with respect to $d_j$ was obtained and denoted as $R_j = \{r_{jd}^{0}, \ldots, r_{jd}^{b}, \ldots, r_{jd}^{c}\}$, where $r_{jd}^{b}$ denoted the $d$th review in $R_j$ and the $b$th one in $R$. $D_j$ represented the size of $R_j$, $a', b', c' \in \{1, 2, \ldots, U\}$.

Second, to identify the sentiment polarities of reviews in $R$, a multi-class classifier based on light-gradient boosting machine (LightGBM) was constructed. LightGBM is a gradient boosting classifier that uses tree-based learning algorithms, which is prevalent in classification tasks due to its faster training speed and higher efficiency (Ke et al., 2017). The labeled dataset $\tilde{R}$ was used to train the sentiment-based classifier. Utilizing the trained sentiment classifier with respect to the $j$th dimension, the semantic polarity of each review in $R_j$ was predicted. Correspondingly, according to the mapping relation between $R_j$ and $R$, the sentiment label of dimension $d_j$ in each review $r_t$ of $R$ was also determined. As a result, the unlabeled review set $R$ was nominally coded like the original review set $\tilde{R}$ as shown in Table 2. Therefore, we merged the two review sets into one coded dataset denoted as $\breve{R} = \{\breve{r}_1, \ldots, \breve{r}_t, \ldots, \breve{r}_T\}$, $t = 1, 2, \ldots, T$, where $\breve{r}_t$ denoted the $t$th coded review. Especially, the reviews in which any predefined dimension was not mentioned were filtered out since they did not involve information about given restaurant attributes.

Third, the nominally coded data were then translated into a structural format as displayed in Table 3. Specifically, let $A = \{A_1, \ldots, A_m, \ldots, A_M\}$, $m = 1, 2, \ldots, M$ denote the service attributes provided in predefined dimensions, where $A_m$ denotes the $m$th restaurant attribute. If the sentiment label of $A_m$ in review $\breve{r}_t$ was positive, then $(A_{mt}^{pos}, A_{mt}^{neu}, A_{mt}^{neg}) = (1, 0, 0)$; if the sentiment label of $A_m$ was neutral, then $(A_{mt}^{pos}, A_{mt}^{neu}, A_{mt}^{neg}) = (0, 1, 0)$; if the sentiment label was negative, then $(A_{mt}^{pos}, A_{mt}^{neu}, A_{mt}^{neg}) = (0, 0, 1)$; if the sentiment label was not mentioned, then $(A_{mt}^{pos}, A_{mt}^{neu}, A_{mt}^{neg}) = (0, 0, 0)$. With regard to the dependent variables, if the sentiment orientation of either CS or RVI in review $\breve{r}_t$ was “Not mentioned”, $\breve{r}_t$ was deleted from the review set due to our purpose to model CS and RVI simultaneously. Further, if the nominal label of CS or RVI in review $\breve{r}_t$ was positive, then it was converted into numerical value 1; if the nominal label was neutral, then the numerical value was 0; if the nominal label was negative, then the numerical value was $-1$. As a result, we obtained the structured data of 274,419 online reviews.

3.4 Modeling the effects of customers’ opinions toward each attribute on CS and RVI

In this part, a bagged neural networks-based model (BNNM) was proposed to model the impacts of customer sentiments toward service attributes on CS and RVI, respectively.
As shown in Figure 2, $K$ sample sets were first drawn from the training dataset according to the sampling strategy. Second, each sample set was used to train a neural network (NN). Third, based on each well-trained NN $k$, the effects of attribute-level performance on the selected dependent variable (SDV) were estimated. Finally, an ensemble strategy was applied to generate more robust effects by aggregating the results of all the NNs. For simplicity, we used SDV to represent the selected predicted target CS or RVI in the following details of the proposed BNNM.

(1) Training dataset

The structure review data of 274,419 restaurant reviews obtained in the last section served as the input samples. Let $x_t = (A_{1t}^{pos}, A_{1t}^{neu}, A_{1t}^{neg}, ..., A_{mt}^{pos}, A_{mt}^{neu}, A_{mt}^{neg}, ..., A_{Mt}^{pos}, A_{Mt}^{neu}, A_{Mt}^{neg})$ denote the attribute-level performance data in review $r_t$, while $y_t$ denotes the value of SDV in $r_t$. The training dataset was then represented as $D = \{(x_1, y_1), ..., (x_t, y_t), ..., (x_T, y_T)\}$, $t = 1, 2, ..., T$.

(2) Sampling strategy

Considering the imbalanced distribution of SDV values in the training set, we first ranked the three sentiment classes according to the numbers of corresponding samples. Then, when establishing each sample subset, we reserved the medium class while conducting the oversampling on the minority and undersampling on the majority. All the sampling actions were with replacement. Finally, we carried out the sampling steps repeatedly and obtained $K$ balanced sample subsets denoted as $D_k = \{(x_{1k}, y_{1k}), ..., (x_{sk}, y_{sk}), ..., (x_{Sk}, y_{Sk})\}$, $s = 1, 2, ..., S$, where $D_k$ denoted the $k$th sample subset, $k = 1, 2, ..., K$.

(3) Constructing the NNs

Considering the complex and nonlinear relationship among restaurant attributes, CS and RVI, we chose NNs as basic prediction units for their powerful capacity in function approximation (Ferrari and Stengel, 2005). Moreover, the effectiveness of NNs in measuring the weights of input variables has been revealed in previous studies (Bi et al., 2019). Specifically, the NN $k$ had a structure of three layers: input, hidden and output, $k = 1, 2, ..., K$. The input was the attribute-level performance, while the output was SDV. In the experimental setup, the hidden layer had $N = 109$ neurons denoted as $\{b_1, b_2, ..., b_N\}$. Further, we built $K = 600$ NNs for each SDV.

**Figure 2.** The framework of the proposed BNNM

*Source(s):* Author’s own creation
(4) Estimating the effects based on each NN

Each constructed NN $k$ was trained using a sample subset $D_k$. When the training process was over, the mean absolute error (MAE) of NN $k$ was determined by Equation (1).

$$MAE_k = \frac{1}{S} \sum_{s=1}^{S} |\hat{y}_{sk} - y_{sk}|$$

(1)

Let $w_{mnk}$ denote the weight between the input neuron $A_m$ and the $n$th hidden neuron $b_n$ of NN $k$, where $m = 1, 2, ..., M$, $n = 1, 2, ..., N$, $\eta \in \Phi = \{pos, neu, neg\}$, $k = 1, 2, ..., K$. Let $w_{nk}$ denote the weight between the $n$th hidden neuron $b_n$ and the output neuron SDV of NN $k$. Let $W_{\eta m k}$ denote the effects of customer sentiments toward service attribute $A_m$ on SDV based on NN $k$, which was calculated according to Equation (2).

$$W_{\eta m k} = \frac{\sum_{n=1}^{N} W_{mnk} \times w_{nk}}{\sum_{m=1}^{M} \sum_{\eta \in \Phi} \sum_{n=1}^{N} |w_{mnk} \times w_{nk}|}, m = 1, 2, ..., M, \eta \in \Phi = \{pos, neu, neg\}$$

(2)

(5) Ensemble strategy

According to the obtained MAE of each NN, the weight $w_k$ of each NN $k$ was computed by Equation (3).

$$w_k = \exp(-MAE_k)$$

(3)

Correspondingly, the normalized weight $\overline{w}_k$ of NN $k$ was calculated by Equation (4).

$$\overline{w}_k = \frac{w_k}{\sum_{k=1}^{K} w_k}$$

(4)

At the end of training of $K$ NNs denoted as $(NN 1, ..., NN k, ..., NN K)$, their normalized weights denoted as $(\overline{w}_1, ..., \overline{w}_k, ..., \overline{w}_K)$ were obtained. Then, we used $\overline{W}_m^\eta$ to denote the aggregated effects of customer sentiment $\eta$ toward the $m$th service attribute on SDV, which was calculated according to Equation (5).

$$\overline{W}_m^\eta = \sum_{k=1}^{K} \overline{w}_k \times W_{mnk}, m = 1, 2, ..., M, \eta \in \Phi = \{pos, neu, neg\}$$

(5)

Using the impacts of customers’ different sentiments toward $A_m$ on SDV, we further estimated the relative importance weight of attribute $A_m$ with respect to SDV. We first calculated the value range of $\overline{W}_m^\eta$, $\eta \in \{pos, neu, neg\}$ using Equation (6). Then, according to Qi et al. (2016) and Bi et al. (2019), the relative importance weight of $A_m$ on SDV was denoted as $\overline{W}_m$ and estimated using Equation (7).

$$Range_m = |\overline{W}_m^{pos} - \overline{W}_m^{neu}| + |\overline{W}_m^{neu} - \overline{W}_m^{neg}|, m = 1, 2, ..., M$$

(6)

$$\overline{W}_m = \frac{\text{Range}_m}{\sum_{m=1}^{M} \text{Range}_m}, m = 1, 2, ..., M$$

(7)

Finally, the relative importance of each service theme was determined by accumulating the importance weights of the service attributes belonging to the theme. For instance, the total effect of service theme food on SDV was determined by $\sum (\overline{W}_{15} + \overline{W}_{16} + \overline{W}_{17} + \overline{W}_{18})$, i.e. the sum of the importance weights of attributes portion size, taste, eye appeal and dish recommendation.
4. Results

4.1 Mining predefined service dimensions from restaurant reviews

According to the process described in Section 3.2, the relevant words toward 20 predefined dimensions were first identified from online reviews as shown in Table 4. Through manual validation, we found that these meaningful words presented high relevance to corresponding service dimensions, indicating the effectiveness of the proposed method. Using the obtained words, we predicted whether each dimension was mentioned in a given restaurant comment. Consequently, the distribution of these dimensions among all the restaurant comments was also determined. The corresponding statistical results are given as follows.

First, Figure 3 illustrates the number of online restaurant comments involving each service attribute. We found that taste was the most frequently mentioned attribute, followed by waiters’ attitude and price level. Moreover, parking convenience was mentioned in the fewest reviews. In summary, the reviews were not equally distributed on these restaurant attributes. Besides, within the final dataset of 274,419 reviews, CS was mentioned in 209,927 reviews, while RVI was in 77,458 reviews. Further, we calculated the number of online comments involving each service theme based on a simple rule. A service theme was regarded as being mentioned in a restaurant review only if at least one of the attributes belonging to the service theme was included in the review. As shown in Figure 4, food was mentioned by the largest number of online reviews, while location occurred in the smallest number of reviews. Besides, the numbers of reviews mentioning service, price and environment were almost equal.

Lastly, we conducted a frequency analysis of the number of service attributes and themes mentioned in a single restaurant comment, respectively. The results in Figure 5 indicate that the number of reviews mentioning two attributes is the largest. Moreover, as the number of attributes mentioned in a single review increased, the number of corresponding reviews decreased. Likewise, a similar pattern was also found in the results regarding service themes as exhibited in Figure 6.

4.2 Measuring customers’ sentiments toward predefined dimensions from restaurant reviews

Based on the sentiment-oriented classifiers built in Section 3.3, customers’ sentiment orientation toward each predefined dimension was determined within each restaurant comment. Figure 7 summarizes these sentiment polarities toward each attribute in all restaurant reviews. As shown in Figure 7, for most of the investigated attributes, the number of positive comments was far larger than the number of neutral or negative ones. Besides, for CS, the numbers of negative, neutral and positive samples were 12,320, 31,149 and 166,458, respectively. Likewise, for RVI, the numbers of corresponding reviews were 7,192, 3,966 and 66,010, respectively. Further, the sum of numerical labels (i.e. converting negative, neutral, and positive into \(-1, 0,\) and 1) of attributes belonging to each service theme in each restaurant review was considered as the sentiment orientation of the corresponding service theme in the given review. The results of Figure 8 indicate that for all service themes, the number of positive reviews was larger than that of negative or neutral ones.

4.3 Estimating the effects of customers’ opinions toward restaurant attributes on CS and RVI

Using the obtained labeled reviews, we estimated the effects of attribute-level performance on CS and RVI based on the BNNM proposed in Section 3.4. The estimated effects of customers’ different sentiments toward each attribute and the relative importance weight for CS and RVI are shown in Tables 5 and 6, respectively. We ranked these attributes by their relative importance weights. Then, a comparison was made between CS and RVI according to their...
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<table>
<thead>
<tr>
<th>Predefined dimensions</th>
<th>Dimension-specific words mined from online restaurant reviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>交通(traffic), 便利(convenient), 地铁(subway), 位置(location), 车站(stop), 位于(located), 公交车站(bus stop)</td>
</tr>
<tr>
<td>$A_2$</td>
<td>广场(plaza), 商场(shopping mall), 位于(located), 百货(department store), 对面(opposite), 商圈(business district), 购物中心(shopping center)</td>
</tr>
<tr>
<td>$A_3$</td>
<td>好找(easy to find), 位置(location), 找到(find), 地理位置(geographic location), 显眼(conspicuous), 醒目(striking), 旁边(next to)</td>
</tr>
<tr>
<td>$A_4$</td>
<td>停车(parking), 停车场(parking lots), 停车位(parking spot), 开车(driving), 免费(free of charge)</td>
</tr>
<tr>
<td>$A_5$</td>
<td>排队(queue), 等位(waiting for a table), 小时(hour) 不用(no need), 分钟(minute), 等到(wait until), 等(wait), 排(line up)</td>
</tr>
<tr>
<td>$A_6$</td>
<td>服务(service), 服务员(waiter), 热情(warm), 服务态度(service attitude), 态度(stance), 主动(proactive), 贴心(attentive), 周到(thoughtful)</td>
</tr>
<tr>
<td>$A_7$</td>
<td>上菜(serving), 速度(speed), 很快(quickly), 分钟(minute), 挺快(pretty quick), 等待(wait), 下单(ordering)</td>
</tr>
<tr>
<td>$A_8$</td>
<td>价格(price), 便宜(cheap), 人均(person per), 价位(price), 不贵(inexpensive), 小贵(little pricy), 块钱(yuan)</td>
</tr>
<tr>
<td>$A_9$</td>
<td>性价比(cost-effectiveness), 算划(cost-effective), 实惠(affordable), 超值(value-added), 经济(economical), 物美价廉(cheap and fine)</td>
</tr>
<tr>
<td>$A_{10}$</td>
<td>团购(group-buying), 霸王餐(dine and dash), 活动(promotions), 优惠(discounts), 代金券(coupon), 打折(discount), 幸运(fortunate)</td>
</tr>
<tr>
<td>$A_{11}$</td>
<td>装修(decorate), 风格(style), 布置(furnish), 装饰(ornament), 灯光(fighting), 装潢(decoration), 情调(mood), 舒适(comfortable)</td>
</tr>
<tr>
<td>$A_{12}$</td>
<td>嗓子(noisy), 安静(quiet), 音乐(music), 吵闹(make noise), 氛围(atmosphere), 气氛(aura)</td>
</tr>
<tr>
<td>$A_{13}$</td>
<td>店面(storefront), 宽敞(spacious), 不大(not big), 空间(space), 面积(area), 拥挤(crowded), 地方(place), 很大(large), 座位(seat)</td>
</tr>
<tr>
<td>$A_{14}$</td>
<td>干净(clean), 整洁(clean and tidy), 卫生(sanitation), 干净的(clean), 苍蝇(flies), 明亮(bright)</td>
</tr>
<tr>
<td>$A_{15}$</td>
<td>分量(portion), 份量(serving size), 个头(size), 很足(generous), 一份(a portion of), 好大(huge), 吃不完(more than can be eaten), 太少(too little)</td>
</tr>
<tr>
<td>$A_{16}$</td>
<td>味道(taste), 好吃(delicious), 口感(mouthfeel), 入味(tasty), 口味(flavor), 好吃的(palatable), 好喝(good to drink), 肉质(fleshy), 浓郁(full-bodied)</td>
</tr>
<tr>
<td>$A_{17}$</td>
<td>外貌(outward appearance), 新鲜(fresh), 精致(delicate), 摆盘(plate presentation), 好看(appealing), 造型(shape), 颜色(color), 食欲(appetite)</td>
</tr>
<tr>
<td>$A_{18}$</td>
<td>推荐(recommend), 强烈推荐(highly recommend), 建议(advise), 必点(must be ordered), 值得(believe), 一试(try), 强推(highly recommend)</td>
</tr>
<tr>
<td>CS</td>
<td>不错(not bad), 喜欢(like), 这家(this), 总体(overall), 满意(satisfied), 这次(this time), 总得来说(in general)</td>
</tr>
</tbody>
</table>

RVI 拜托(next time), 再来(again), 还会(again), 光顾(visit), 还会(revisit), 朋友(friend), 尝试(try), 第二次(again), 机会(chance) |

Source(s): Author's own creation

rankings of attributes as shown in Table 7, which underlines the most salient attribute for each service theme.

As displayed in Table 7, taste, waiters' attitude, cleanliness of facilities and cost effectiveness were the top four important attributes, no matter whether the dependent variable was CS or RVI. Moreover, each of the top attributes was also the most important attribute regarding the service theme to which it belonged. For service theme location, the most important attribute of CS was the distance from business districts while that of RVI was traffic convenience. The transition indicates that convenient transportation played a crucial role in attracting restaurant patrons to make a return decision. Furthermore, except for traffic convenience, the attributes which had an improved ranking from CS to RVI included portion size, ambient conditions, price discount, cost effectiveness, wait time and parking convenience.
Lastly, for a service theme, its relative importance was determined by accumulating the weights of the attributes belonging to the theme. As such, a hierarchical importance order of service themes and attributes was obtained. Table 8 displays the weights and rankings of five service themes for CS and RVI. We found that regarding CS, the importance order of these themes was food, environment, service, price and location, while the order for RVI was food, service, environment, price and location. Despite the almost same rankings, the weights of food and environment decreased while that of price and location increased when comparing RVI to CS.

5. Discussion
This study analyzed large-scale online restaurant reviews derived from DianPing.com and proposed a novel supervised framework to model the effects of attribute-level performance on CS and RVI simultaneously. Methodologically, an effective method of mining the dining experience from online reviews was introduced. Theoretically, the ample findings revealed by the current
research will benefit researchers and practitioners for a more complete and comprehensive understanding of the dining experience.

First, our results indicate food was the most frequently mentioned service theme in online reviews, which is congruent with previous studies (Bilgihan et al., 2018; Tian et al., 2021). This finding is intuitive considering food is the primary product of a restaurant. Besides, we found that the majority of the reviews just mentioned no more than three themes. As such, customers mentioned food most frequently since food is the main purpose of dining out. Moreover, we found that food was the most salient service theme affecting both CS and RVI. The results indicate that food is king, despite the complexity of dining experience (Pantelidis, 2010).
Second, for RVI, the strongest effect of food is not in agreement with Yan et al. (2015) suggesting that service has the greatest effect. The potential explanation is that the attributes of food and service in the two studies are partially different, resulting in the various effects of the corresponding service themes. For CS, food and environment were the most two important service themes, followed by service, price and location, which is inconsistent with Gan et al. (2017) on the ranking of environment. In this study, the service theme environment not only contained the atmosphere and the mental environment but also incorporated the physical environment such as facilities and decoration. As such, the impact of the environment was more salient than that in previous research. In sum, the inconclusive hierarchal order of service themes still needs more academic attempts in future research.

Third, location has been scarcely investigated in prior work. In this study, when comparing RVI to CS, the weight of location increased, suggesting the relative importance of
**IMDS 1235**

<table>
<thead>
<tr>
<th>Service themes</th>
<th>Restaurant attributes</th>
<th>CS</th>
<th>RVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>Traffic convenience</td>
<td>16</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Distance from business districts</td>
<td>13</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>Easiness to find</td>
<td>14</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>Parking convenience</td>
<td>17</td>
<td>14</td>
</tr>
<tr>
<td>Service</td>
<td>Wait time</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Waiters’ attitude</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Serving speed</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Price</td>
<td>Price level</td>
<td>15</td>
<td>15</td>
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<td></td>
<td>Cost effectiveness</td>
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<td>3</td>
</tr>
<tr>
<td></td>
<td>Price discount</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>Environment</td>
<td>Interior decoration</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Ambient conditions</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Spatial layout</td>
<td>12</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Cleanness of facilities</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Food</td>
<td>Portion size</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Taste</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Eye appeal</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Dish recommendation</td>
<td>7</td>
<td>8</td>
</tr>
</tbody>
</table>

**Table 5.**
The effects of attribute-level performance on CS obtained by BNNM

Source(s): Author’s own creation

<table>
<thead>
<tr>
<th>Attribute</th>
<th>$W^{pos}$</th>
<th>$W^{neg}$</th>
<th>$W^{ave}$</th>
<th>$W^{avg}$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
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<td>$A_1$</td>
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<td>-0.0006</td>
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</tr>
<tr>
<td>$A_2$</td>
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<td>-0.0007</td>
<td>-0.0022</td>
<td>0.0215</td>
<td>$A_{11}$</td>
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<tr>
<td>$A_3$</td>
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<td>-0.0006</td>
<td>-0.0015</td>
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</tr>
<tr>
<td>$A_4$</td>
<td>0.0013</td>
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<td>-0.0008</td>
<td>0.0151</td>
<td>$A_{13}$</td>
</tr>
<tr>
<td>$A_5$</td>
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<td>-0.0010</td>
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<tr>
<td>$A_6$</td>
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<td>-0.0055</td>
<td>-0.0222</td>
<td>0.1509</td>
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</tr>
<tr>
<td>$A_7$</td>
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<td>-0.0060</td>
<td>0.0455</td>
<td>$A_{16}$</td>
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<tr>
<td>$A_8$</td>
<td>0.0007</td>
<td>-0.0003</td>
<td>-0.0015</td>
<td>0.0153</td>
<td>$A_{17}$</td>
</tr>
<tr>
<td>$A_9$</td>
<td>0.0028</td>
<td>-0.0012</td>
<td>-0.0082</td>
<td>0.0781</td>
<td>$A_{18}$</td>
</tr>
</tbody>
</table>

**Table 6.**
The effects of attribute-level performance on RVI obtained by BNNM

Source(s): Author’s own creation

<table>
<thead>
<tr>
<th>Attribute</th>
<th>$W^{pos}$</th>
<th>$W^{neg}$</th>
<th>$W^{ave}$</th>
<th>$W^{avg}$</th>
<th>$W$</th>
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</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>$A_2$</td>
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<td>-0.0004</td>
<td>-0.0001</td>
<td>0.0182</td>
<td>$A_{11}$</td>
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<tr>
<td>$A_3$</td>
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<td>0.0065</td>
<td>0.0065</td>
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<tr>
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<td>0.0018</td>
<td>0.0320</td>
<td>$A_{13}$</td>
</tr>
<tr>
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<td>-0.0015</td>
<td>0.0207</td>
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<td>$A_6$</td>
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<td>$A_{15}$</td>
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<tr>
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<td>$A_{17}$</td>
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<tr>
<td>$A_9$</td>
<td>0.0029</td>
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<td>-0.0037</td>
<td>0.1067</td>
<td>$A_{18}$</td>
</tr>
</tbody>
</table>

**Table 7.**
Comparison between the rankings of service attributes with respect to CS and RVI

Source(s): Author’s own creation
location in attracting restaurant patrons' revisit activities. Despite its bottom position in the ranking of five themes, the role of location should not be neglected. Therefore, more attention should be paid to the definition, measurement and estimation of location (Wong and Zhao, 2016).

Lastly, different from most previous studies focusing on the importance order of just service themes, we constructed a hierarchical importance order comprising both service themes and attributes. Our results open up promising avenues for understanding the factors influencing CS and RVI from whole to part.

6. Implications
6.1 Theoretical implications
Theoretically, our contributions to hospitality and service literature are two-fold: First, prior research mainly gathered multifaceted consumer opinions using surveys or interviews. However, due to the huge cost of data collection, it is difficult to keep up with the constantly shifting restaurant business. Our research demonstrates that online reviews bear the potential of serving as an alternative data source in solving service-related issues. We explore the potential of the online data sources in resolving service-related issues. Our results demonstrate the great advantages of collective wisdom embedded in online reviews in terms of representing the dining experience and modelling CS and RVI, which will expand the hospitality research scope. Second, we are one of the first studies to mine attribute-level performance, CS and RVI simultaneously from online reviews. Moreover, we established a hierarchical structure of eighteen attributes within five service themes and estimated their effects on both CS and RVI. In sum, our research will broaden the understanding of customer perception and behavioral intention in the process of service consumption.

Methodologically, the employed text analytics and machine learning techniques enable academic researchers and industry participants to tap the power of online reviews in terms of understanding the time-varying consumer experience and formulating dynamic operation strategies. The proposed research framework mines dining experience, CS and behavioral intention from textual reviews and establishes relationships among them and each other. The experiment results demonstrate the effectiveness of the framework, which could be used in similar subsequent research scenarios.

6.2 Practical implications
This study also has managerial implications for restauranteurs. First, we detected the attributes that customers are most concerned with and customers' positive, neutral and negative toward these attributes, which can be regarded as the attribute-level performance of restaurant services. Restaurant managers might be able to turn a dissatisfied customer back through a managerial response involving targeted content such as improvement measures

<table>
<thead>
<tr>
<th>Service themes</th>
<th>CS Weight</th>
<th>CS Rank</th>
<th>RVI Weight</th>
<th>RVI Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>0.0695</td>
<td>5</td>
<td>0.1136</td>
<td>5</td>
</tr>
<tr>
<td>Service</td>
<td>0.2049</td>
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<td>0.2046</td>
<td>2</td>
</tr>
<tr>
<td>Price</td>
<td>0.1485</td>
<td>4</td>
<td>0.1909</td>
<td>4</td>
</tr>
<tr>
<td>Environment</td>
<td>0.2177</td>
<td>2</td>
<td>0.1917</td>
<td>3</td>
</tr>
<tr>
<td>Food</td>
<td>0.3594</td>
<td>1</td>
<td>0.2992</td>
<td>1</td>
</tr>
</tbody>
</table>

Source(s): Author’s own creation

Table 8. Comparison between the weights and rankings of service themes with respect to CS and RVI.
Second, we established the importance order of the five service themes, which allows restaurant owners to optimize resource allocation and gain competitive advantages. Furthermore, the most salient attribute for each service theme was also identified. It has implications for small and medium-sized restaurants which have limited operating capital. These restaurants might still have a successful performance by paying the majority of their attention to the attributes that are most associated with CS and RVI.

The current research has also practical implications for customers and platforms. According to our results, consumers can compare their own particular service attribute preference with collective ranking, which will help them to choose the best-matched restaurant even if it is not the most popular restaurant with the highest rating scores. At the same time, when they post online reviews after consumption, they can adjust the content according to our results. The customers who share high-quality comments will get coupons from platforms or restaurants. Platforms can rank the restaurants according to the obtained service attribute rankings, which will facilitate their users to choose the best service provider and in turn increase the user stickiness. Finally, the platforms can use the proposed method to design their ranking algorithm which can calculate the real-time rankings of restaurants.

7. Conclusion
Building on the extensive literature on dining experience and the promising potential of online reviews, this study purposed a novel research framework to model CS and RVI simultaneously from online restaurant reviews. More specifically, we first established the content distribution of each predefined dimension from online reviews using a supervised method based on random forest. Then, the sentiment polarities of the reviews toward the predefined dimensions were identified using LightGBM. Finally, the effects of attribute-specific sentiments on CS and RVI were evaluated by BNNM.

The current research is not without limitations, which may serve as directions for future research. First, in the sampling stage, we did not consider the different restaurant types (e.g. full-service, fast food, etc.). Therefore, our findings derived from the collected online reviews are aggregated results of diverse restaurant segments. By gathering the review data of the target restaurant type, exclusive management insights for the target restaurant type can be obtained using the proposed framework. Second, there might exist fake reviews in our online review dataset, which will lead to inaccurate results. Prior work has uncovered that tourism managers are motivated enough to manipulate online content. Thus, future studies should consider fake review detection to obtain spontaneously generated comments. Finally, considering the impact of cultural origin on the dining experience, the established hierarchal order of restaurant attributes in our work could be tested in diverse catering cultures.

References


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