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What Affects the Online Ratings of Restaurant Consumers: A Research Perspective on Text-mining Big Data Analysis

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Abstract

Purpose: Despite a significant focus on customer evaluation and sentiment analysis, limited attention has been paid to discrete emotional perspective in terms of the emotionality used in text. This paper aims to extend the general-sentiment dictionary in Chinese to a restaurant-domain-specific dictionary, visualize spatiotemporal sentiment trends, identify the main discrete emotions that affect customers' rating in a restaurant setting, and identify constituents of influential emotions.

Design/methodology/approach: A total of 683,610 online restaurant reviews downloaded from Dianping.com were analyzed by a sentiment dictionary optimized by the authors; the main emotions (joy, love, trust, anger, sadness, and surprise) that affect online ratings were explored by using multiple linear regression methods. After tracking these sentiment review texts, Latent Dirichlet Allocation (LDA) and LDA models with term frequency-inverse document frequency (TF-IDF) as weights were used to find the factors that constitute influential emotions.

Findings: The results show that it is viable to optimize or expand sentiment dictionary by word similarity. The findings highlight that love and anger have the highest effect on online ratings. The main factors that constitute consumers' anger (local characteristics, incorrect food portions, and unobtrusive location) and love (comfortable dining atmosphere, obvious local characteristics, and complete supporting services) are identified. Different from previous studies, negativity bias is not observed, which poses a question of whether it has to do with Chinese culture.

Practical implications: These findings can help managers monitor the true quality of restaurant service in an area on time. Based on the results, restaurant operators can better decide which aspects they should pay more attention to; platforms can operate better, and can have more manageable webpage settings; and consumers can easily capture the quality of restaurants to make better purchase decisions.

Originality/value: This study builds upon the existing general sentiment dictionary in Chinese and, to the authors' knowledge, is first to provide a restaurant-domain-specific sentiment dictionary and utilize it for analysis. It also reveals the constituents of two prominent emotions (love and anger) in the case of restaurant reviews.

Keywords: Sentiment analysis; Text-mining; Online reviews; Latent Dirichlet Allocation; Restaurant; Restaurant domain lexicon
Paper type: Research paper
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1. Introduction

In recent years, due to the rapid development of online comment networks, a large amount of ratings or comments generated by consumers in the restaurant industry has been appearing in the online comment world (Xiang *et al.,* 2017). The impact of the number of online reviews and online ratings on product sales or business revenue has been confirmed by several studies (Torres *et al.*, 2015; Zhao *et al.*, 2015; Stylos *et al.*, 2021). The influence of online reviews on consumer purchase decisions is also attracting attention. Gretzel and Yoo (2008) found that approximately 74% of travel decisions are made in reference to online reviews. Lu *et al.* (2015) concluded that review content has a greater impact on consumer purchase decisions compared to online ratings. Accordingly, the textual comments have gradually drawn the attention of industry operators and managers who wish to find ways to improve online ratings in a timely manner (Tian *et al.,* 2021).

Not surprisingly, research into sentiment analysis and emotions has gained significant popularity in hospitality and tourism (Mehraliyev *et al.*, 2022; Nusair, 2020; Gour *et al.*, 2021; Mariani and Baggio *et al.*, 2021). Scholars have established the perceived quality-emotion-behavioural intention model, wherein quality includes product quality, atmosphere, and service quality, while emotion includes both positive and negative emotions. Through this model, they demonstrated that emotions mediate the impact of perceived quality on behavioral intention (Ribeiro and Prayag, 2019). Recently, Rocklage *et al.* (2021) concluded that emotionality in text may be more indicative of the success of a product or service compared to average star rating.

This research aims to contribute to sentiment analysis research by covering several research gaps. The existing methods of evaluating consumer emotions focus mainly on binary classification (i.e., positive versus negative), or on a certain type of emotional state (e.g. happy or angry). There is a lack of a multidimensional approach to sentiment analysis. Such an approach is important because human emotions are complex and diverse, containing not only positive and negative (Mathayomchan and Taecharungroj, 2020; Tian *et al.*, 2021) but also discrete emotions. Examples of such approach include that of Ekman (1972) (anger, disgust, fear, joy, sadness, and surprise) and the categorization of six basic emotions by Shaver *et al.* (1987) (anger, fear, joy, love, sadness, and surprise), which are rarely used in hospitality research.

Another important contribution of this project is the provision of a sentiment dictionary specific to the restaurant domain. Sentiment analysis can be widely divided into lexicon-based (or dictionary-based) and machine learning (or statistical) approaches, each with its own advantages and disadvantages. The statistical approach requires a substantial amount of manual classification of training data and therefore is time-consuming. While the lexicon-based approach is time-efficient, its performance is highly dependent on the domain. General sentiment dictionaries cannot fully capture the emotions and sentiments available in, for example, hotel, restaurant, or film reviews. Although domain-specific dictionaries are crucial for high accuracy of sentiment analysis, to the best of authors' knowledge, restaurant-specific sentiment dictionaries are not yet available. This paper builds upon previous research to create a sentiment dictionary specific to the restaurant domain and uses it to perform sentiment analysis in restaurant reviews.

The effect of emotions on consumer evaluation has been tested in various areas but rarely in a restaurant context. Lin *et al.* (2014) found that there were five emotions in tourism setting: pleasure, joy, pride, love, and interest. Hosany and Gilbert (2010) showed that the emotional experience of tourists consisted of pleasure, surprise, and love. Nawijn *et al.* (2016) found that tourist emotions in dark tourism scenarios are pain, sympathy, and positive emotions. Little is known in the case of restaurant reviews about the effects of various emotions on review evaluation. In their study of restaurant consumers, Oh and Kim (2021) found that joy, sadness, disgust, surprise, and anger were closely related to service, food, and reputation. However, the authors did not test the relationship between emotion categories and online ratings. On these grounds, it is timely to examine the effect of discrete emotions on online ratings.

Once the main emotions that affect online ratings are identified, the next step is to examine the components of influential emotions. Recent study by Mehraliyev *et al.* (2020) called researchers to use data mining techniques and examine unstructured data to reveal the constituents of various variables. This paper responds to this call and contributes to hospitality research by investigating the factors that constitute most influential discrete emotions.

To summarize, this study aims to fill the gaps from the following aspects. The first gap is domain-specific. To the best of authors' knowledge, there is no restaurant-adapt-specific sentiment dictionary. Accordingly, the paper aims to enhance existing general sentiment dictionaries in Chinese and extend it to the restaurant domain. Second, little is known about the spatiotemporal trends of restaurant sentiments. In this regard, the second aim is to visualize and examine such trends and discuss their theoretical implications. Third, most tourism and hospitality research focuses on polarity categories (positive or negative) for sentiment analysis or exploring individual sentiments, rarely paying attention to a series of discrete emotions. It is still unclear which discrete emotions affect online restaurant ratings. Accordingly, this paper aims to statistically test the effect of discrete emotions on consumer ratings in a restaurant setting. Fourth, little is known about what constitutes specific discrete emotions in restaurant reviews. Thus, the fourth aim is to perform topic clustering on the most influential emotions and identify their components or main factors. The final gap we aim to cover is contextual. There are limited sentiment analysis studies in hospitality in Chinese. Given some scholars' (Cohen and Cohen, 2012, Mehraliyev *et al.*, 2019) growing concerns on the applicability of tourism and hospitality knowledge developed in the western world to the eastern cultures and societies, the authors believe that the outcomes of this study will be an important reference point for Asian hospitality scholarship.

2. Literature review

2.1 Online ratings

Customers use online ratings to post their reviews or opinions about goods and services, which have a significant impact on consumer behavior in making purchase decisions. As mentioned by Jiang *et al.* (2021), 6% of online reviews can influence nearly 50% of consumer decisions, while 90% of consumers browse online reviews before purchasing a product, and nearly half of consumers rely on review information for their purchase decisions. Similarly, Mathwick and Mosteller (2017) found that 20-50% of purchase decisions were made according to online ratings. Consequently, understanding how guests achieve certain ratings and which areas should be improved accordingly is a primary task for both companies and researchers (Zhu *et al.*, 2020; Gao *et al.*, 2018).

Research on the factors influencing online ratings has been highlighted in many areas. Scholars concluded that some determinant factors of accommodation ratings are rank (Radojevic *et al.*, 2015), the certification of quality management (Heras-Saizarbitoria *et al.*, 2015), and power distance (Gao *et al.*, 2018). Other studies found that opinions of friends (Lee *et al.*, 2017) and reviewers' personality (Gao *et al.*, 2017) may affect online ratings. Moreover, Engler *et al.* (2015) confirmed that online product ratings are affected by pre-purchase expectations and a product's post-purchase performance.

Faced with the sheer volume of big data, traditional questionnaires or self-report surveys are becoming less applicable. Among the many research perspectives, emotionality in text attracted researchers' attention. Many scholars attempted to find more information from emotions. For instance, Zhu *et al.* (2020) explored the relationship between sentiments and online rating, and found that positive (negative) sentiment is associated with a high (low) rating. Tsaur and Pei-Chun (2020) explored the memorable dining experience from the perspective of emotions and further analyzed the factors contributing to it. But the relationship between emotionality in text and online rating is still unknown.

2.2 Emotionality in text

As mentioned above, emotionality in text is already in the research spotlight; research from an effective perspective is also in full swing. Previous research concluded that there exist three theoretical approaches to classifying emotions (Wu and Gao, 2019). The first approach is binary polarity detection, which differentiates sentiment as positive or negative (Mathayomchan and Taecharungroj, 2020; Tian *et al.*, 2021). However, this approach conceals important differences between different emotions and does not provide accurate evaluation of products or services posted by consumers, as it oversimplifies complex human emotions to only two classes. On this basis, the second approach is to distinguish the extent of positive or negative emotions. A straightforward classification in this line of research is strong positive, positive, neutral, strong negative, and negative emotions according to their intensity (Baccianella, 2010). The third approach relies on the psychology of emotions. Accordingly, sentiment refers to mental state when people encounter a specific object, event, or person and can be divided into a series of basic *discrete* emotions, such as anger, fear, guilt, joy, sadness and surprise (Izard and Carroll, 1977; Plutchik, 2000).

Among discrete emotion classifications, Ekman's six basic emotions were the most popular in computer science research (Yadollahi *et al.*, 2017), which comprises anger, disgust, fear, joy, sadness, and surprise (Ekman, 1972). There have been several attempts to complete and/or enhance Ekman's classification, such as Shaver et al.'s six basic emotions (i.e., anger, fear, joy, love, sadness, surprise) and Plutchik's (2000) circumplex emotion model. **Table I** shows some of the sentiment classifications referenced in this study.

Table I Some representative classifications

Sentiment classification	Article
anger, disgust, fear, joy, sadness, surprise	Ekman,1972
anger, fear, joy, love, sadness, surprise	Shaver *et al.*,1987
joy, trust, fear, surprise, sadness, disgust, anger, anticipation	Plutchik,2000

Besides Ekman's (1972) six basic emotions (i.e., anger, disgust, fear, joy, sadness, and surprise) and Shaver *et al.*'s (1987) six basic emotions (i.e., anger, fear, joy, love, sadness, surprise), Zhang and Zhang (2017) applied grounded theory to analyze the emotions (e.g., amazing, fear, joy) of tourists riding into Tibet based on semi-structured interviews. Different emotions have different effects on consumer evaluation. In this regard, scholars have also confirmed that regret and anxiety are related to post-purchase behaviors (Zeelenberg and Pieters, 2004), while happiness, relaxation, and anger are connected to visitor satisfaction (Wu and Gao, 2019). Hosany and Gilbert (2010) found that joy, love, and positive surprise are an important part of visitors' emotions.

Many scholars have begun to explore which discrete emotions may influence online consumer evaluations, including online ratings. Faullant *et al.* (2011) confirmed that emotions associated with consumption are joy and fear. Wu and Chang (2020) selected three negative emotions: anger, sadness, and fear in a study of customer reviews of online retailers. Evidently, previous research supports that positive emotions raise customers' scores, while negative emotions lower them (Zhu *et al.*, 2020). The same can be applied to a restaurant context to hypothesize relationships between discrete emotions and online ratings. When it comes to the choice of discrete emotion categories, this paper opts to follow recommendations by Shaver *et al.* (1987) mainly for methodological reasons explained in detail in section 4.1. Accordingly, this paper proposes six hypotheses as follows:

H1: Joy has a significant positive effect on online ratings.

H2: Love has a significant positive effect on online ratings.

H3: Trust has a significant positive effect on online ratings.

H4: Surprise has a significant positive effect on online ratings.

H5: Anger has a significant negative effect on online ratings.

H6: Sadness has a significant negative effect on online ratings.

2.3 Sentiment analysis

Sentiment analysis provides a way to quickly recognize and extract emotions and views from text (Birjali *et al.,* 2021; Chaturvedi *et al.*, 2018). At present, mainstream sentiment analysis can be divided into lexicon-based, machine learning, and hybrid methods. Lexicon analysis uses a sentiment dictionary to judge the expected sentiment information; sentiment words in the sentiment dictionary are matched with the sentiment words in the text to be processed (Jurek *et al*., 2015). Machine learning is used to train the algorithm with sentiment data that has been labeled in advance; the algorithm then predicts the sentiment tendency of the remaining text after training. Hybrid methods have been very popular in natural language processing, which uses dictionaries for sentiment recognition and machine learning for polarity detection. Each method has its relative merits (Cambria, 2016; Acheampong *et al*., 2020).

Although some argue that machine learning is more accurate than lexicon-based sentiment analysis (Yadav and Roychoudhury, 2019), it requires manual annotation of a large number of corpora as a training set. When the amount of labelled data is insufficient to train a machine learning classifier, it is easy to produce data sparsity and classification errors (Song *et al.,* 2020), which application is limited to certain fields, and it is not appropriate for tourism phenomena *(*Liu *et al.,* 2019). Some scholars argue that hybrid methods are the best way to perform sentiment computation and sentiment analysis, compensating for the shortcomings of lexicon-based and machine learning (Cambria, 2016). However, recent research that uses hybrid methods has mainly focused on binary polarity detection, which has limited explanatory power in the realm of discrete emotion (Shaukat *et al*., 2020; Tao *et al*., 2019). Another problem is that hybrid methods often face difficulty in choosing deep learning techniques (Acheampong *et al*., 2020). The lexicon-based sentiment analysis method has the advantage of universality (Mukhtar *et al.*, 2018), and it can easily and quickly identify the categories of sentiment words in the text. However, the difficulty is that it requires considerable effort and time to establish sentiment dictionaries for different fields.

In this paper, researchers opt to use a lexicon-based approach mainly for the following two reasons. The first reason is its relevance to the objectives, i.e., the demand of discrete sentiment analysis and the application of tourism phenomena (Liu *et al.*, 2019). The second is that there almost does not exist a labeled dataset in Chinese restaurant context, which makes machine learning approach or hybrid methods substantially time-consuming. Third, lexicon-based sentiment analysis is popular and frequently used in tourism and hospitality research (Alaei *et al.*, 2019; Nie *et al.,* 2020). Ren and Hong (2017) proposed a method for sentiment classification of online reviews at the topic level using a sentiment dictionary and focusing on the analysis of specific emotions on customer complaints. Oh and Kim (2021) analyzed online reviews of restaurants in Hong Kong based on Plutchik's (2000) circumplex emotion model. With the scope of these studies being limited to English situations, little attention was made to Chinese context, with limited knowledge of the relationship between basic emotions and star ratings requiring further studies.

2.4 Factors influencing emotions

Emotional information in online reviews can reflect a consumer's emotional experience while dining in restaurants, which can be affected by many factors, such as intangible elements and subjective experiences (Tsaur and Pei-Chun, 2020). Studies have been conducted to confirm the impact of physical environment such as lighting (Liu and Jang, 2009) and music (Bruner, 1990) on customer mood. Wu and Gao (2019) confirmed that in addition to physical environment, service management, products, and interpersonal interactions also affect the sentiment of restaurant customers. A beautiful environment, high-quality service, and employees' positive emotions can stimulate customers' positive emotions; crowded dining spaces are more likely to cause customers' negative emotions (Quan *et al*., 2021). The restaurant atmosphere also significantly affects customers' willingness to spread positive word-of-mouth and satisfaction (Rabbow, 2021; Liu and Jang, 2009; Heung and Gu, 2012).

The impact of personal factors (e.g. cultural difference) on the mood of the meal should not be ignored. Customers with different cultural backgrounds devote different amounts of attention to the key points in restaurants, and the factors that stimulate their emotions are also different (Jia, 2020; Oh *et al*., 2019; Ying *et al*., 2020). For instance, American customers are more concerned about the quality of food, while Korean customers are more concerned about the physical environment (Oh *et al*., 2019).

Despite their valuable contribution, data on the factors that influence or constitute customer emotions mainly comes from offline interviews or questionnaire surveys.

Although some researchers proposed and improved models to measure consumer-related emotions, such as the M-R model (Mehrabian and Russell, 1974; Peng *et al.*, 2017; Liu and Jang, 2009), those models or analysis techniques have limited applications when facing a large amount of data. With the expansion of online reviews and textual data sources, different clustering algorithms provide a reference for exploring influencing factors, such as topic modeling (Kwon *et al.*, 2021; Fang and Partovi, 2021), Latent Dirichlet Allocation model (Liu and Beldona, 2021), semantic network analysis (Oh and Kim, 2021). Therefore, this paper not only highlights the main factors through a discrete emotion perspective, but takes a data-driven approach and performs the Latent Dirichlet Allocation model to identify what constitutes these emotions.

3. Data collection

To achieve its purpose, this study obtained restaurant review data from 2004 to 2021 from the third-party review platform, Dianping, within the boundaries of Chunxi Road Street, using the city of Chengdu as an example. The following explains the reasons researchers chose Chengdu and Dianping as a research setting.

3.1 Why Chengdu?

Chengdu is an important city in western China. It has been known as the “land of abundance” since ancient times and is one of the top ten tourist cities in China. The development of tourism and the restaurant industry in Chengdu ranks at the forefront of the country, especially Chunxi Road Street in the prosperous Jinjiang District. This street was hailed as the first commercial street in the Midwest and the first merchant highland in the Midwest. Since its development, Chunxi Road has become a testament to the prosperity and development of Chengdu, and it is regarded as a “landmark” of Chengdu. Therefore, we selected the Chunxi Road business district (an area with a radius of approximately 1.5 km around the Chunxi Road landmark) to conduct restaurant service quality research.

3.2 Why Dianping?

Our data comes from China's leading local life information and trading platform and the world’s first independent third-party consumer comment website—Dianping. As of 2017, Dianping.com covered 2,298 (80%) county-level management agencies across the country (Dong *et al*., 2019). In this study, we obtained detailed information (consumption reviews and addresses) for 677 restaurants in the Chunxi Road business district from the Dianping platform. We carried out data screening and preliminary processing to assess the feasibility and accuracy of the data analysis. First, restaurants with fewer than 200 reviews since the opening were excluded; second, the restaurants that had ceased operations were excluded (businesses that were closed as of the date of data acquisition). As a result, data includes a total of 341 restaurants covering reviews in the period from August 2, 2004 to March 17, 2021. This includes 683,610 online reviews, of which 682,889 reviews have valid ratings.

4. Methodology

Figure 1 illustrates the research flow for this project. First, to collect data in the Chinese context, this study utilized web crawlers that collect data from Dianping.com. Owing to the big dataset, this study adapted sentiment analysis to perform text-mining analysis. Second, to get discrete sentiment and make it more appropriate, this study extended the sentiment vocabulary ontology database of Dalian University of Technology by a word similarity algorithm, then reconsidered the emotion categories based on previous literature and empirical observation of data. Third, spatiotemporal trends of the mapped sentiments were revealed through visualization. Fourth, in order to test a relationship between emotions and online ratings, multiple regression analyses were conducted. Ultimately, subject clustering was conducted to disclose factors that constitute specific basic emotions (i.e. those that are influential predictors of consumer rating).

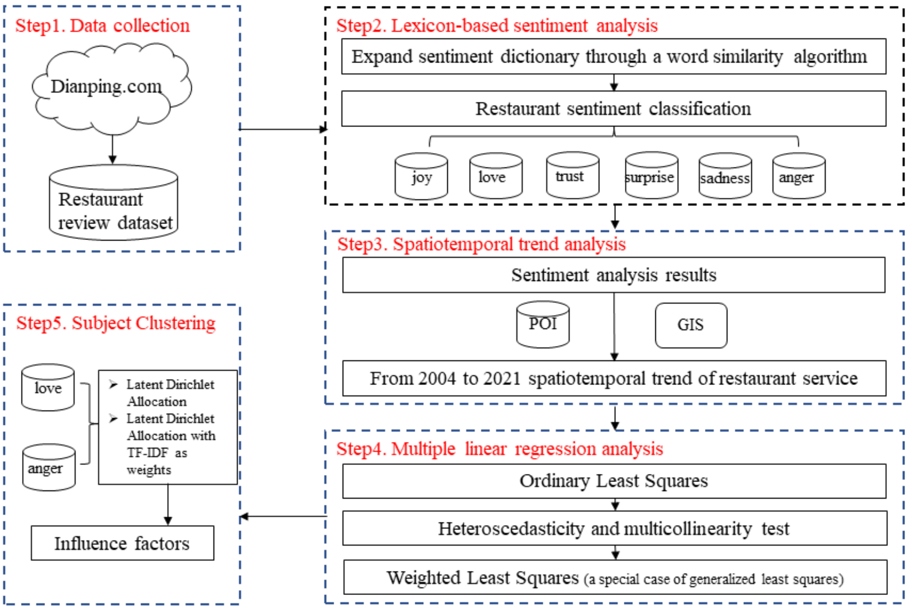

Figure 1 Research flow

4.1 Lexicon-based sentiment analysis

A sentiment dictionary comprises a series of emotion words labeled based on certain rules which varies across national language contexts. In the English context, popular sentiment dictionaries include SentiWordNet 3.0 (Baccianella *et al*., 2010), NRC (Al-Fares *et al*., 2010), and HowNet dictionary (Dong and Dong, 2001). Popular dictionaries used in the Chinese context mainly include the HowNet dictionary (Dong and Dong, 2001), the NTUSD dictionary of Taiwan University, Li Jun's commendatory and derogatory dictionary of Tsinghua University, the sentiment vocabulary ontology database of Dalian University of Technology, and the Boson dictionary.

There are already some attempts to expand sentiment dictionaries to make it more suitable for the new language environment. Liu *et al*. (2019) expanded the HowNet sentiment dictionary through manual reading travel logs and tourist online reviews, but this study only considered the tourism domain. Du (2013) used a word similarity algorithm for dictionary matching and fusion, focusing on social media platform (i.e., Sina Weibo). Considering the rapid development of third-party review sites and the continuous emergence of online terms, this paper added the Boson dictionary by word similarity algorithm. Here, Boson dictionary is a sentiment polarity dictionary automatically built from millions of sentiments annotated data from microblogs, news, forums, and other data sources. Then, this paper referred to the construct of a tourism-specific lexicon to develop a restaurant-specific lexicon to enhance suitability (as described below in more detail).

The sentiment vocabulary ontology database of Dalian University of Technology was launched by Xu *et al*. (2007). This sentiment dictionary is built based on Ekman's six categories of emotion classification system (i.e. anger, disgust, fear, joy, sadness, surprise), which has been influential overseas. In view of Ekman's system, this dictionary added the seventh emotion category – good – to the vocabulary ontology. The emotions in the vocabulary ontology are divided into seven major categories (anger, disgust, fear, joy, good, sadness, surprise), 21 sub-categories, and contain 27,466 words in total (see **Table II**).

Table II Lexicon Composition

Number	Major categories	Sub-categories
1	anger	anger
2	disgust	boredom, abhorrence, denounce, jealousy, doubt
3	fear	panic, fear, shame
4	joy	joy, reliable
5	good	respect, praise, trust, love, wish
6	sadness	sadness, disappointment, guilt, miss
7	surprise	surprise

The optimization process is carried out through several steps which draw on the literature (Du, 2013), as shown in **Figure 2**. First, this paper compared the big data of comments obtained from the public comment platform to eliminate rare words; 27,212 words remained. Second, the Boson dictionary applicable to the social media platform was added to the basic sentiment dictionary according to a word similarity calculation algorithm based on HowNet, after which the total number of vocabulary words was 30,149. Third, the latest internet terms and restaurant vocabulary (145 words from 10,000 reviews) on the Dianping platform were added. Finally, the relevance of each word proposed by word similarity calculations was manually checked, and some were eliminated; the improved dictionary had a total of 29,321 words.

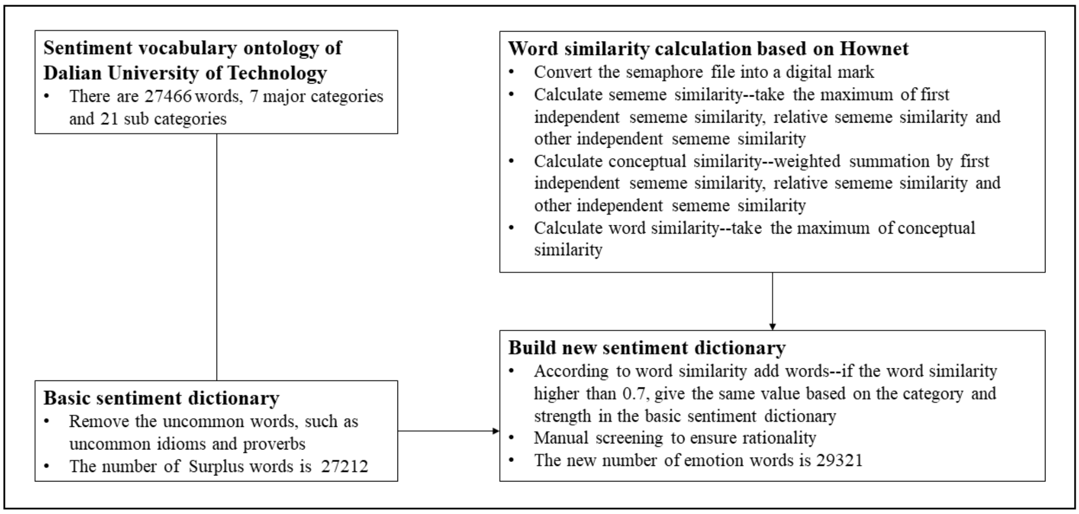

Figure 2 Lexicon optimization steps

Joy, anger, sadness, and surprise were retained in this sentiment dictionary according to Ekman's sentiment model. Considering previous literature (Shaver *et al*., 1987; Hosany and Gilbert, 2010; Chen and Phou, 2013) and words in the dictionary, the major category "good" was renamed as "love". Further changes were performed based on observations and individual assessments by researchers. Particularly, to assure the reliability and appropriateness of the Chinese language, researchers checked several reviews in the dataset to perform relevant re-categorization if needed. The sub-categories "reliable" and "trust" were combined and renamed as "trust", to match their ontological meaning in Chinese. Previous research confirmed that "fear" was rarely mentioned (Hosany and Gilbert, 2010; Oh and Kim, 2021); similar observations were found in our dataset and hence, this category was deleted. Although it has been shown that disgust affects customer satisfaction (Wu and Chang, 2020; Oh and Kim, 2021), Hosany and Gilbert (2010) found that only joy, love, positive surprise may influence the tourist experience. Our observation of reviews showed that combining "anger" with "disgust" is more appropriate. After the analysis above, the final categories used in this study for sentiment analysis were joy, love, trust, surprise, sadness, and anger.

Further changes were made to the process of sentiment analysis with respect to the addition of negative words and degree adverbs, as they changed the sentiment category and sentiment score (Polanyi and Zaenen, 2006; Du, 2013). The negative word dictionary (70 words in total) and degree adverb dictionary (276 words in total) were established by integrating the studies of Du (2013) and Xu *et al*. (2007). The following equation shows how to process negative words and degree adverbs before sentiment words. In this equation, w_{ij} is the intensity value of the i-th sentiment word belonging to category j in the sentence; m represents the number of negative words; n represents the adverbs of degree; and $f(n)$ represents the weight of adverbs of different degrees in the degree adverb dictionary.

$$Sentiment\ score\ (w,m,n) = \begin{cases} \sum_{j=1}^{n} \max(w_{ij}) * f(n), & m\ is\ even \\ -\sum_{j=1}^{n} \max(w_{ij}) * f(n), & m\ is\ odd \end{cases}$$

In addition, as shown in **Table III**, if the sentiment intensity is negative, the sentiment category changes. Similar to the antonym spoken in the Chinese context, the emotion expressed in the phrase "this restaurant has a good amount of food" is joy, while the emotion expressed in the phrase "this restaurant has a very small amount of food" is anger after adding the negative word; "The decoration is beautiful" expresses love, while the addition of negation expresses disappointment.

Table III Sentiment category conversion

Origin sentiment category	Origin sentiment score	New sentiment category	New sentiment score
Joy (if<0)	a	Anger	O(anger)+a
Love (if<0)	a	sadness	O(sadness)+a
Trust (if<0)	a	Anger	O(anger)+a
Surprise (if<0)	a	-	-
Sadness (if>0)	a	Joy	O(joy)+(-0.2)*a
Anger (if>0)	a	Love	O(love)+(-0.3)*a

Note: a is an example score, $O(x)$ is the origin sentiment score of x.

After manually reviewing nearly 1,000 restaurant reviews (Du ,2013), an in-depth discussion was conducted by five participants to discriminate the sentiment after adding negatives to each. The following conclusions were reached: When the initial sentiment category is joy, negative intensity converts it to anger, and the sentiment score is accumulated directly. In the same manner, the initial sentiment categories "love" and "trust" would be converted to "sadness" and "anger" in the presence of negative intensity, and the sentiment score will accrue directly. When the initial emotion type is surprise, there is no specific sentiment after adding the negation. When the initial sentiment category is sadness, negative intensity converts it to joy, and the sentiment score is multiplied by -0.2 (the sentiment score of sadness is less than 0); it is accumulated to joy. When the initial sentiment category is anger, its category is converted to love, and the sentiment score is multiplied by -0.3 and accumulated to love. Among them, 0.2 and 0.3 are determined through repeated experiments according to Du (2013).

4.2 Subject Clustering and Perplexity

We used unsupervised machine learning techniques to explore the topics or subjects in different sentiment categories. TF-IDF is a classic text keyword extraction algorithm to measure the semantic importance of the word in the text. It calculates the weight of feature words using their term frequency and inverse document frequency, as shown in the following equation:

$$TFIDF(d_i, t_i) = TF(d_i, t_i) * \lg\left(\frac{M}{DF(t_i)}\right) = TF(d_i, t_i) * IDF(t_i)$$

where $TF\left(d_i, t_i\right)$ represents the number of times the feature word d_i appears in the current text d_i; $DF(t_i)$ represents the number of texts that appear in the text data set t_i; M is the total number of texts in the text data set; and $IDF(t_i)$ is the inverse document frequency, which is lg $\left(\frac{M}{DF(t_i)}\right)$.

The LDA topic model is a three-level Bayesian model which is an unsupervised machine learning technology that can present the topic of each text in the form of a probability distribution. And it is regularly used in the field of information retrieval for large-scale text hidden topic recognition (Blei *et al.*, 2003). Each document i in corpus D is assumed to have the following generation process: 1. Let $N \sim \text{Poisson}(\theta)$, assuming that the words in the dictionary follow the Poisson distribution. 2. Let $\theta \sim Dir(\xi)$, assuming that θ follows a Dirichlet distribution in which the parameter is α; θ_i represents the proportion of each topic contained in document i, which also means the topic distribution of document i. 3. For each word w_n in N, we first assign topics according to θ_i and obtain the topic $z_{i,n}$ of word n in document i, which also means the topic distribution z_n of sample word n, and then word w_n is sampled from the word distribution corresponding to the assigned topic. This process is repeated until all the documents are completed.

The perplexity index is used to evaluate the quality of topic clustering. Perplexity is a measurement method of information theory (Blei *et al.*, 2003). It is an index to measure the optimal number of topic clusters in the LDA model. The lower the degree of perplexity, the better the effect of the model on the number of topics divided by topic clustering. The calculation equation of perplexity is as follows:

$$Perplexity(D) = exp\left\{\frac{\sum_{d=1}^{M} logp(W_d)}{\sum_{d=1}^{M} N_d}\right\}$$

where D represents the test set in the data set; there are a total of M texts; N_d represents the number of words in each text d; W_d represents the words in each text d; and $p(W_d)$ is the probability of the word W_d being generated.

5. Results

5.1 Sentiment dictionary optimization result verification

The verification of the dictionary optimization results was carried out through manual sampling by the project team. This involved randomly selecting 1,000 of the 682,889 observations and verifying the sentiment score and sentiment category. The 1,000 texts were randomly assigned to five project team members, who were asked to assess each of the results. If there were any ambiguities in understanding, the texts were placed in the disputed text database. After the assessments were completed, the texts in the disputed text database were distributed to each member, and the results were determined by the consensus reached by half of the members. The results were then manually compared with the optimized dictionary results to verify that they were consistent.

The optimization effect is mainly reflected in the following aspects: First, the optimized results show more accuracy in emotion recognition. "Very professional," "help with rice mixing," "serving fast," "fried chicken is delicious," and "yummy" show the high evaluation of the dining experience. The original category was "good", and the degree was slightly weaker. "Al dente," "not so fabulous," "disappointed," indicate dissatisfaction with service. "The waiter training is a bit poor" expresses anger. Second, it is reflected in the recognition of new vocabulary, especially in the new language environment, such as "must be praised," "thumb-up," and "just-so-so". In general, the optimized sentiment dictionary has improved the accuracy of sentiment category recognition and the numerical accuracy of sentiment scores, which can be used in the restaurant context.

5.2 Spatiotemporal trend of restaurant service

The second objective of this paper was to visualize spatiotemporal trends. The sentiment scores calculated by the sentiment analysis reflect the service quality of the restaurant. The average total sentiment score was calculated for every five years from 2004 to 2021 and combined with ArcGIS to produce a grid visualization with a grid size of 50*50 m. The results indicate that: from 2004 to 2008 (**Figure 3**, part b), the proportion of restaurants in the study area receiving "excellent" and "good" was 18.2%; from 2009 to 2013 (**Figure 3**, part c), the sentiment scores slightly increased, but the proportion of restaurants receiving "excellent" and "good" decreased to 11.4%, which may be because of the rapid increase in the number of restaurants (i.e. doubled in this period). From 2014 to 2018 (**Figure 3**, part d), the sentiment score also increased, and the proportion of restaurants receiving "excellent" and "good" remains decreasing (8.1%); it shows the same trend as the number of restaurants tripled. From 2019 to 2021 (**Figure 3**, part e), the sentiment score increased substantially, and the proportion of restaurants receiving "excellent" and "good" had a dramatic increase to 18.7% due to the gradually stabilizing number of restaurants.

In terms of space, the total sentiment score (**Figure 3**, part a) shows a decreasing trend from south to north and from west to east. The more concentrated the tourist attractions, the higher the total sentiment score of the restaurant. Consistent with the fact that restaurants near tourist attractions are mostly boutiques. The map also shows three areas that need to be focused on, including the middle of the East Street, northwest of the Shudu Road and northwest of the Yushuang Road. The distribution of total sentiment scores at different stages shows that while there are increasingly more restaurants in the Chunxi Road business district of Chengdu, the service quality of the restaurant is also improving with an increasing number of boutique restaurants.

Figure 3 The spatial and temporal pattern analysis of sentiment score from 2004 to 2021 Note: (a) The total sentiment score. (b) The sentiment score from 2004 to 2008. (c) The sentiment score from 2009 to 2013. (d) The sentiment score from 2014 to 2018. (e) The sentiment score from 2019 to 2021.

5.3 Effect of basic emotions on online ratings

The restaurant ratings from the Dianping platform are entered as the dependent variable, and the independent variables were the sentiment indicators of the chosen basic emotions (i.e. joy, love, trust, surprise, sadness, and anger) in multiple linear regression analysis. The models are estimated in *Stata* to show the contribution of different emotions to online ratings. **Table IV** lists the average sentiment scores for each sentiment category. Among them, love had the highest sentiment score (19.7461), indicating that customers expressed love more than other emotions in the review text. This was followed by trust (3.7251), joy (2.4685), anger (1.1280),and surprise (0.2462). However, in general, customers seem to be fairly satisfied with the service quality of restaurants in the Chunxi Road business district in Chengdu.

Table IV Data description

Sentiment category	Mean	Sd
Joy	2.4685	0.9817
Love	19.7461	4.5522
Trust	3.7251	0.9729
Surprise	0.2462	0.0924
Sadness	0.3567	0.1711
Anger	1.1280	0.3421

Regression analysis was performed on rating behavior to test the contribution of each sentiment category (see **Table V**). The R^2value for the overall model is 0.28, which is higher than the recommended thresholds of 0.10 (Falk and Miller, 1992), 0.13 (Cohen, 1977) and even higher than 0.20 (Hair et al., 2011). Subsequently, the Breusch-Pagan test and the White test were performed to assess the presence of heteroscedasticity. The results were inconsistent, which can be considered an indication of heteroscedasticity (see **Table VI**). We also tested for the presence of multicollinearity. The variance inflation factor (VIF) test was used. The mean VIF score was 1.72, and the VIF of each variable was less than 10, indicating that there is no multicollinearity. Then, the heteroscedasticity correction was performed using the weighted least squares (WLS), and the corrected results are shown in **Table VII**.

Table V Regression analysis result ($R^2 = 0.28$)

Sentiment category	Coef	P>|t|
Lnjoy	0.0420	0.001**
Lnlove	0.1154	0.000**
Lntrust	0.0147	0.474
Lnsurprise	-0.0161	0.057
Lnsadness	-0.0106	0.233
Lnanger	-0.0801	0.000**

Note: lnx means take the logarithm of x, ** indicates significant correlation at the 0.01 level (two-tailed).

Table VI Heteroscedasticity analysis

Examination method	Chi2	P>Chi2
Breusch-Pagan test	0.03	0.8664
White test	44.68	0.0176

Table VII WLS analysis ($R^2 = 0.25$)

Sentiment category	Coef	P>|t|
Lnjoy	0.0197	0.148
Lnlove	0.1299	0.000**
Lntrust	0.0282	0.120
Lnsurprise	-0.0208	0.024**
Lnsadness	-0.0045	0.644
Lnanger	-0.0650	0.000**

Note: Ln indicates that log-transformation was performed on variables;
** indicates statistical significance at the 0.01 level (two-tailed).

After the above steps, a model of the contribution of the different emotion categories to online ratings was established. The model shows that anger, love, and surprise have a significant impact on online ratings. This is consistent with the results of Zhu *et al.* (2020), then also demonstrates our H1, H3 and H5 were rejected, while H2, H4, H6 were supported. Among the different emotions, the effect of love was the strongest (0.1299), indicating that comments expressing high evaluation in customer reviews will significantly improve the overall ratings of the restaurant. Anger had the second strongest effect (-0.0650), indicating that when customers feel anger during the consumption process, they give the restaurants lower ratings.

The result that the effect of love is much higher than anger was in line with the evaluation preferences of Chinese people. Because of traditional habits and individual preferences, Chinese restaurant customers are not inclined to assign low scores to restaurant services (Jia, 2020). Another interesting finding is that surprise has a notable negative effect on online ratings. With regards to this, we returned to the text of the comment containing the surprise and concluded that there exists positive surprise (e.g., “This dish is simply amazingly delicious”) and negative surprise (e.g. “Shocked to have to wait so long in line”), which was confirmed in previous research (Hosany and Gilbert, 2010).

5.4 Topic clustering on most influential emotions

As mentioned above, we have implemented discrete sentiment analysis of text and determined which emotions significantly affect online ratings. To explore the factors constituting emotion, this study adapted the sensory dimension classifier of Mehraliyev *et al.* (2020) and established a text classification (see **Figure 4**) to track back comment texts of different emotions. The text classification shows text that contains a specific type of emotion.

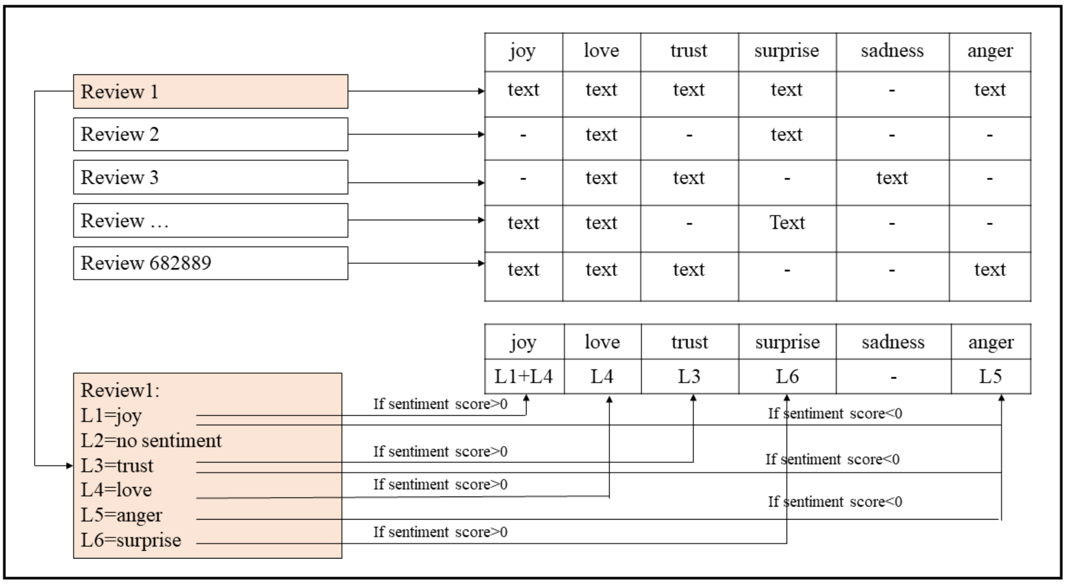

Figure 4 The process of text classification

Mehraliyev *et al.* (2020) referred to this method as “sentiment scales” or “textual constructs” and called future researchers for further improvements. While traditional constructs consist of measurement items, textual constructs are made of unstructured texts. For example, sentences that include emotional words explaining joy, may be extracted, and concatenated together to form a textual construct of joy. One particular research direction they suggested was to reveal the constituents of textual constructs. This paper conducted subject-clustering techniques to understand these constructions better. To this end, the following steps were performed. After obtaining the text library of different emotions, the researchers loaded a custom dictionary, performed text segmentation, removed stop words, and retained nouns for text vectorization. Two models were used for text subject clustering. The first is Doc2bow vectorization and text subject clustering (LDA). Second, TF-IDF was used as the weight in text subject clustering (see **Figure 5**). Finally, the model with the smallest degree of perplexity is the best model, as mentioned in Section 4.3.

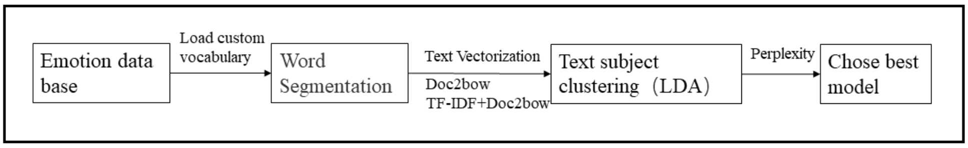

Figure 5 The process of text subject clustering

The clustering was performed only on the most influential positive and the most influential negative emotions, which are love and anger, respectively, as identified in the previous step. When carrying out the subject clustering of anger according to the principle of minimum perplexity (see **Figure 6**), the first model was selected as the best clustering model, and the optimal number of topics was three. When carrying out love subject clustering (see **Figure 7**), according to the principle of minimum perplexity, the first model was selected as the optimal clustering model, and the optimal number of topics was three.

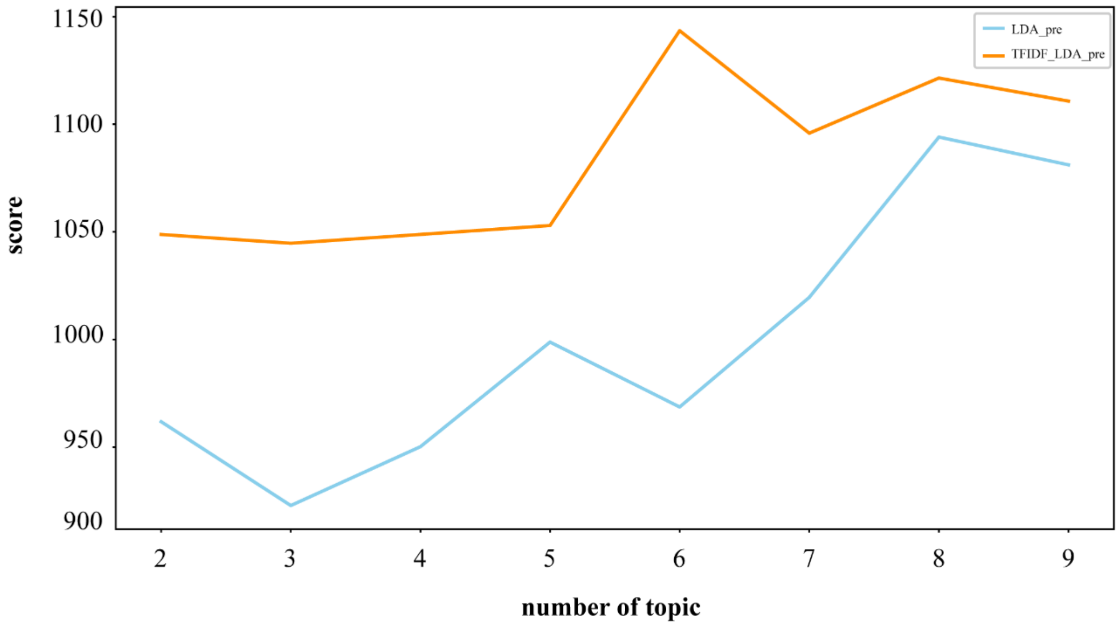

Figure 6 The perplexity of first model

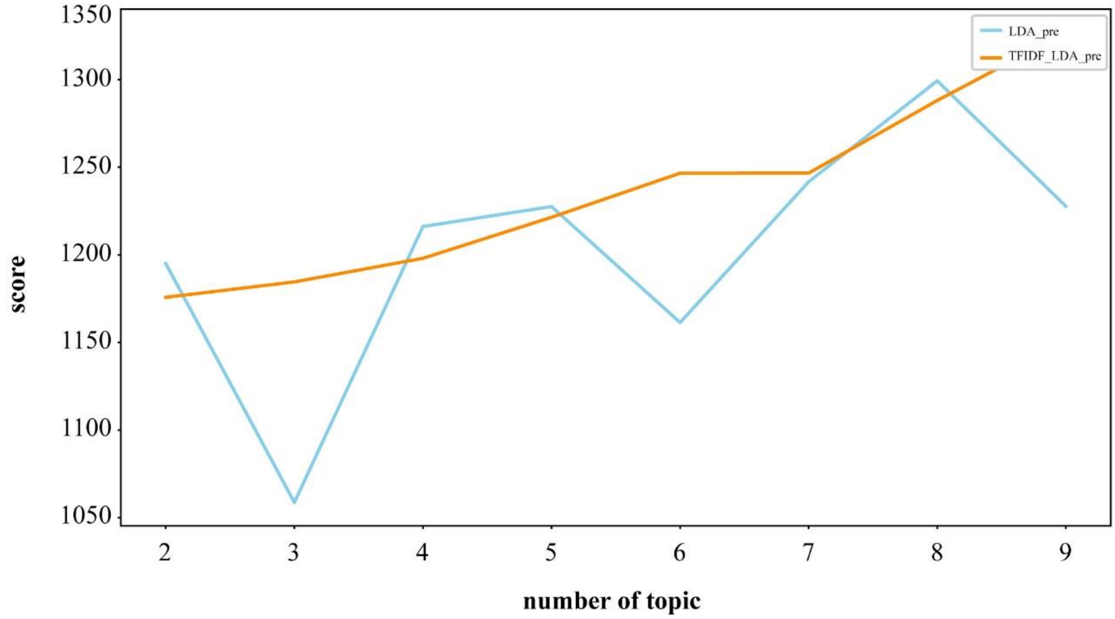

Figure 7 The perplexity of second model

The following figures visualize the results of LDA clustering (Sievert and Shirley,2014). The circle on the left represents the number of clustered topics; the circle size represents the marginal topic distribution; red is the current topic. While the rectangular bar on the right part represents the 30 related topic words under the current topic, and the length of the rectangular bar represents the predicted word frequency size. The results show three topics for anger, which are unacceptable local characteristics (**Figure 8**), incorrect food portions (**Figure 9**), and unobtrusive location (**Figure 10**).

In the first theme, keywords such as “Sichuan cuisine,” “Chengdu,” and “spicy” indicate that the spicy taste of Sichuan cuisine will cause discomfort among customers who don't like spicy food. While “rabbit” (may be related to rabbit meat) appears because some people find it hard to take. However, long queues due to the overcrowded people may arouse anger among foreign tourists who value their time. In the second theme, keywords such as “price,” “weight,” “a little,” “personal,” “too much,” indicated that the meals were too small and expensive, which are inappropriate for large gatherings and one person. This can easily cause anger for customers who do not understand the size of the portion. In the third theme, keywords such as “store,” “ancient town,” “tianfu square,” and “public” indicated that there were too many dining spots in the popular area, making it difficult to search according to location in Dianping.com. When consumers find it difficult to search restaurants, they are more likely to feel anger during the subsequent restaurant services.

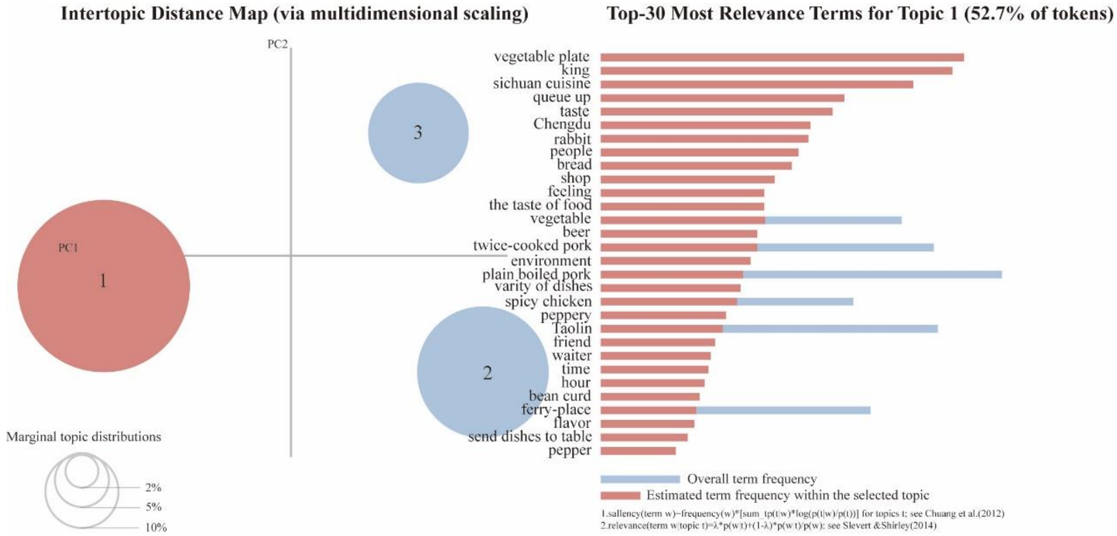

Figure 8 The first LDA clustering result of anger

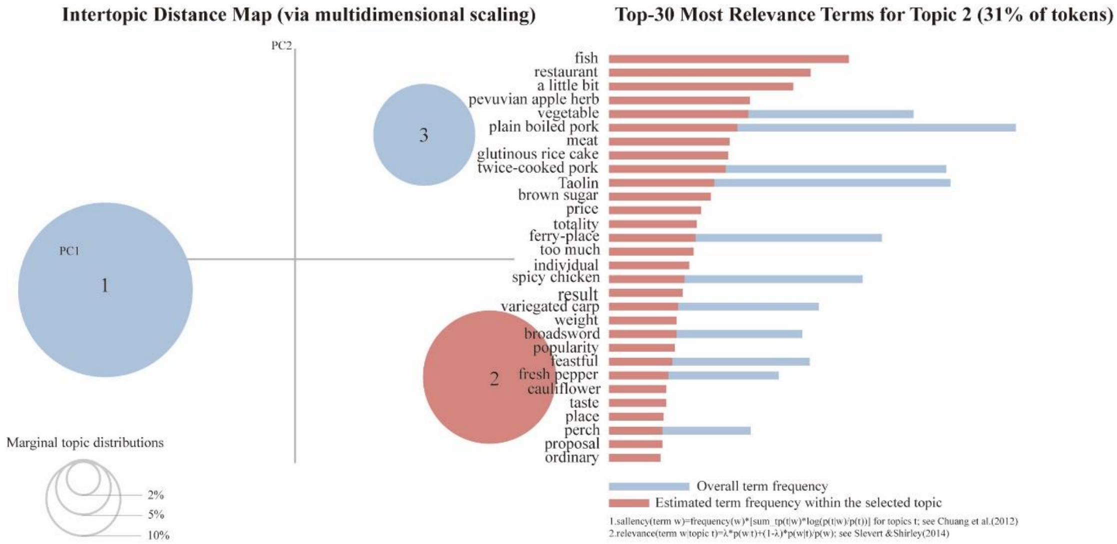

Figure 9 The second LDA clustering result of anger

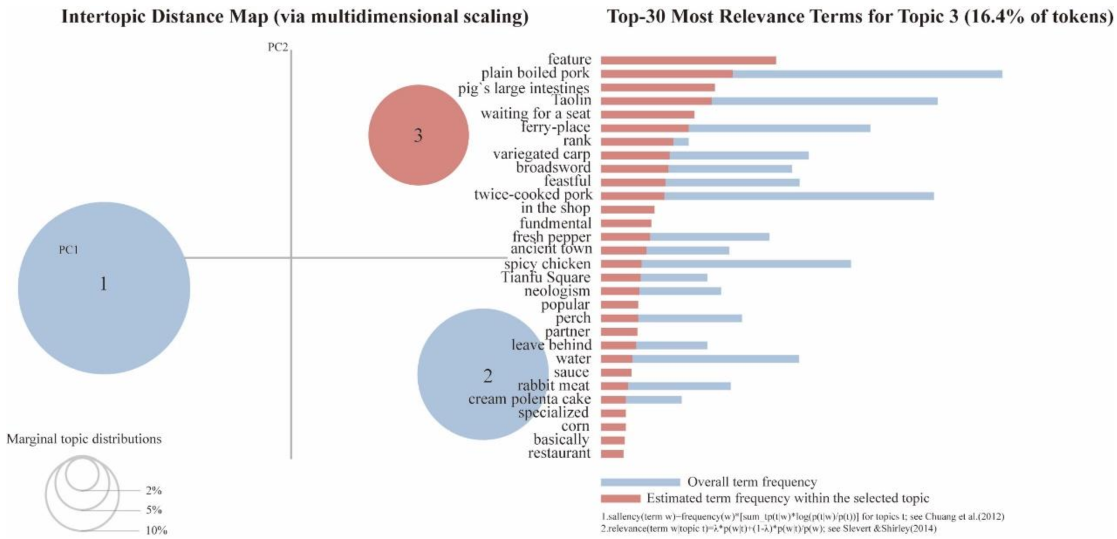

Figure 10 The third LDA clustering result of anger

The LDA clustering results for love demonstrate that there were three topics: a comfortable dining atmosphere (**Figure 11**), prominent local characteristics (**Figure 12**), and complete supporting services (**Figure 13**). In the first theme, keywords such as “features,” “restaurants,” “friends,” and “beers” implied that the restaurants met the requirements of a gathering atmosphere for a group of friends, which can greatly enhance consumers’ love of restaurants. In the second theme, keywords such as “Sichuan cuisine,” “Chengdu,” “rabbit,” “taste,” “spicy,” showed that consumers who like spicy food may be fond of the restaurant's offerings. In the third theme, “egg rolls,” “cone,” “Alipay” indicated that desserts after a meal and convenient payment methods made consumers pay attention to the restaurant, develop a strong opinion, and assign higher online ratings.

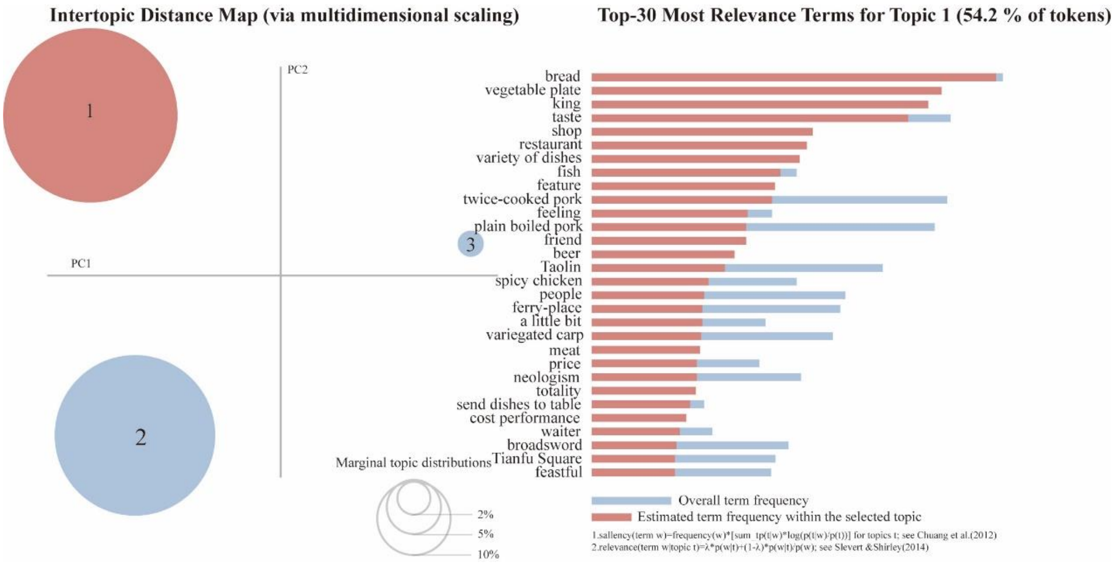

Figure 11 The first LDA clustering result of love

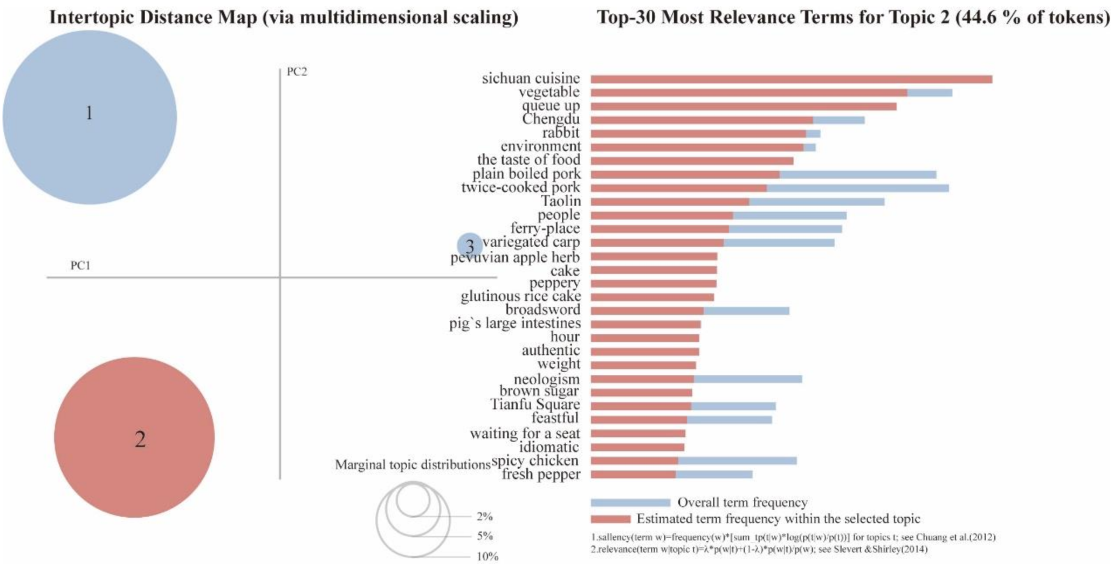

Figure 12 The second LDA clustering result of love

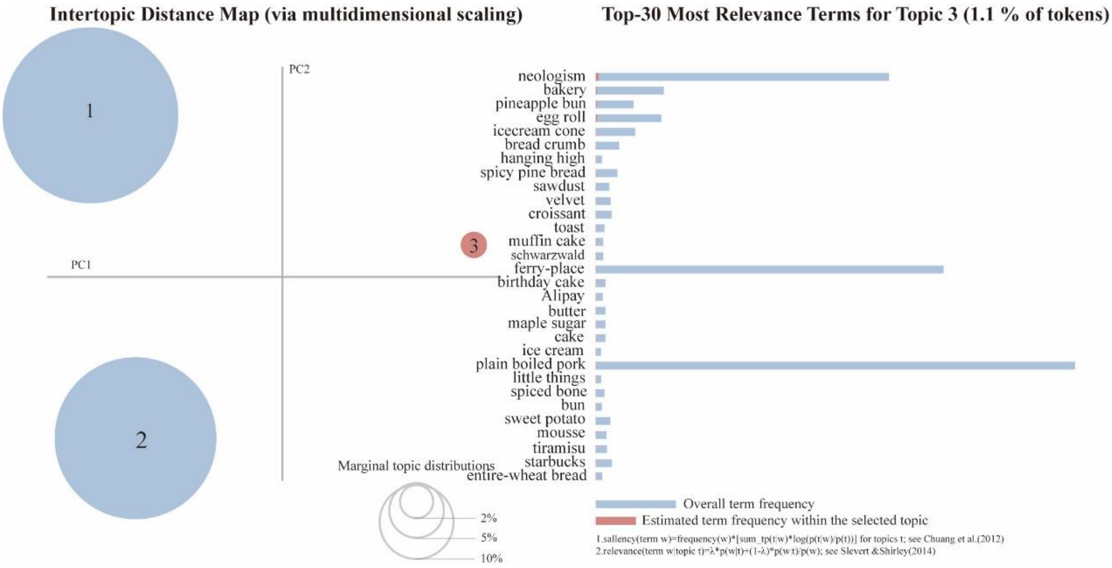

Figure 13 The third LDA clustering result of love

6. Discussions

6.1 Methodological implications

The first objective of this paper was to optimize the Dalian University of Technology sentiment vocabulary ontology library based on big data through word similarity calculation algorithm. Herein lies the first methodological contribution of this paper. The results show that optimization works well, and the algorithm can be used to expand sentiment dictionaries. However, individual assessment of the proposed words is necessary before performing any additions to the sentiment dictionary. As our observations revealed, automatic calculations propose both relevant and irrelevant additions. The improvement performed does not necessarily mean that the proposed dictionary is universally better than the original dictionary for all domains. While this improvement was performed for the hospitality domain, especially with a focus on restaurants, further improvements could be made for other domains. The proposed method can be used to develop similar domain-specific dictionaries (e.g., hotel setting) in English or other languages.

The fourth objective was to find the constituents of the most influential positive and negative emotions, in this case, love and anger. It has both methodological and theoretical contributions. From a methodological perspective, using the subject clustering method to extract features or topics from the text database of different emotions is different from the earlier methods, such as high-frequency words.

6.2 Theoretical implications

The extended dictionary has a valuable theoretical contribution. To the best of the authors' knowledge, it is the first restaurant-domain-specific sentiment dictionary. It may serve as a guide for future studies to perform discrete sentiment classification. Given the notable rapid increase and development in Asian tourism and hospitality scholarship (Cohen and Cohen, 2012), this study will likely be an important reference point for future sentiment analysis research in Chinese.

The second objective of this paper was to visualize spatiotemporal trends with respect to sentiment scores in a restaurant context. One interesting observation was that as the number of restaurants stabilizes, the share of excellent and good scores starts to increase. Furthermore, the highest scores could be observed in restaurants in tourist spots. Implications of this trend contribute to knowledge by posing intriguing questions to hospitality and tourism geographers. For example, can parallels be drawn between spatiotemporal sentiment trends and how Butler's (1980) touristic area develops? The period covered in this study shows a dramatic increase in the number of restaurants, consistent with Butler's development stage. As the increase stabilizes, the share of excellent ratings also increases. A potential explanation could be that towards the end of the development stage, restaurants with poor service simply cannot compete and thus fail, while those with better services continue to function; hence, overall sentiment scores become higher towards the end of this stage. Arguably, such analysis can be used to predict critical turning points and identify changes from one stage to another. While our data is limited for conclusive arguments, the findings seem to identify a potential change from development stage towards consolidation. Future research with biggerdata and longer timespans in different destinations may help to reveal different stages and life cycles.

Concerning the third objective, this paper identified statistically significant predictors of online ratings by using basic emotions as independent variables. Hospitality researchers have used different emotion models for sentiment analysis (Faullant *et al.*, 2011; Uzir *et al.*, 2021; Chen and Phou, 2013; Wu and Chang, 2020; Oh and Kim, 2021). The findings of this paper demonstrate that love, surprise, and anger are significant predictors of online ratings. As could be expected, love and anger have positive and negative effects on customer ratings, respectively. An interesting observation is that love has a higher effect than anger. Our findings contribute to debates on positivity/negativity bias based on prospect theory. Particularly, our findings are not consistent with the findings of Lai *et al.* (2021) (negative sentiment scores result in a greater drop in online hotel ratings than positive sentiment scores). The difference may be explained by Chinese culture that people usually give higher scores than consumers of other nationalities (Jia, 2020). So, an intriguing question is whether positivity bias exists in online restaurant reviews in Chinese context.

Another interesting variable that requires further research is "surprise" which surprisingly had a negative effect on online ratings. Further observations showed that surprise yields both positive and negative sentiments. An important future research direction is recategorizing surprise emotion into distinct positive and negative surprise categories. This line of research may further elaborate how the effects of positive and negative surprises differ. In this regard, our finding pinpoints to and is in line with previous research based on prospect theory which implies that the effect of negative emotions is higher than the effect of positive ones.

In terms of theoretical contribution, the paper reveals topics that constitute or influence anger and love. In the case of anger, the topics are i) unacceptable local characteristics, ii) incorrect food portions, and iii) unobtrusive location; with respect to love, the revealed topics are i) comfortable dining atmosphere, ii) obvious local characteristics, and iii) complete supporting services. Some of the topics in online reviews identified in previous literature are location (Han *et al.*, 2020; Zardi *et al.*, 2018), dining atmosphere (Rabbow, 2021; Heung and Gu, 2012; Ha and Jang, 2010) and local characteristics (Erkmen, 2019). Supporting services and food portions are new findings in this paper. This paper also extends Mehraliyev *et al.*'s (2020) discussions on textual constructs by proposing a method for revealing their constituents. Unstructured text in online reviews may have several hidden textual constructs, each of which has its own components. The proposed technique can be used to understand such textual constructs better. As for further research, authors may consider comparing themes revealed in a textual construct with the measurement items of relevant variables.

6.3 Practical implications

From the operator's point of view, customer reviews of what has been consumed are crucial for the operator to develop a marketing strategy. Our findings show that love can lead to higher customer ratings, while anger and negative surprise can lead to the opposite result. Therefore, operators should pay attention to enhancing customers' love for the restaurant when conducting marketing campaigns and restaurant operations, reduce the spread of customers' anger through some service compensation measures (Liu *et al*, 2020). This study further identifies the components of love and anger in a restaurant setting and shows how to consolidate customers' affection and avoid anger. Particularly, practitioners should consider enhancing the local characteristics of the food, offering authentic flavors and creating a good dining atmosphere. This may be complemented by targeted marketing to filter market segments, timely reminders of food flavors, reasonable consideration of food portion settings, as well as timely updates on restaurant locations in review platforms and the selection of obvious signposts as a basis for location finding in order to reduce customers' anger.

For review platforms, the individual ratings provided by review platforms include taste, service, and environment (some include ingredients) and do not fully cover the main dimensions such as the picture of the restaurant appearance (to make it easy to find), dining atmosphere, and food portions. These dimensions could be added to the website so that consumers can visualize the quality of the food service offered by the restaurant, make more rational purchasing decisions, and improve the experience of using the platform.

From a managerial perspective, these findings can help managers better understand restaurant quality from customers' perspectives as observed in their reviews. Finding reliable information from many text reviews is not easy for managers. The results of our study can provide a reliable basis for destination managers to grasp the level of evaluation of regional restaurant service. Used in conjunction with spatial visualization, it can facilitate managers to grasp the historical evaluation trends of a region and monitor the quality of the regional restaurant experience in real-time. Based on it, destination managers can quickly identify the typical areas (e.g. excellent or not), promote the experience of excellent regions in a timely manner, and focus attention and remediation on poorly evaluated regions.

7. Conclusion

Consumers tend to make consumption decisions based on restaurant ratings and reviews (Mathayomchan and Taecharungroj, 2020; Meek *et al*., 2021; Zhu *et al*., 2020; Kwon *et al*., 2021). Researchers have found that in contrast to online ratings, potential consumers often refer to reviews from other customers who have already spent money making purchase decisions (Kwon *et al*., 2021). Among other things, the emotion in the text may be more indicative of the success of the product or service (Rocklage *et al*., 2021). Moreover, in emotional psychology, there are different types of emotions, which are discrete (Izard and Carroll, 1977; Plutchik, 2000). Based on this rationale, we assume that different types of sentiment have different effects on online ratings and argue that there may be several emotions that significantly impact online ratings. The literature review above shows that limited big-data research noted this gap.

This study provided an optimized sentiment dictionary for a restaurant context in Chinese language, showed methodological techniques on how to do so (potentially applicable to other domains), identified emotions that have a significant effect on the ratings based on an optimized sentiment dictionary, and used clustering to better understand the constituents of these emotions (potentially applicable to other textual constructs). It finally concluded the “must-be” works (Ranjbari *et al*., 2020) for improving online ratings.

8. Limitations and Future research

Although our research contributes to sentiment analysis research in restaurants, there are still some limitations. First, our empirical study is based on 683,610 restaurant reviews in Chunxi Street, Chengdu. While the sample size is sufficiently large, it may not reflect the pattern of regional development, and future consideration could be given to expanding the sample size to obtain more objective pattern characteristics. Furthermore, the setting of transfer coefficients may require further verifications when it comes to negative sentiment transfer. The settings of 0.2 and 0.3 were judged by manual identification based on the repeated experiments conducted and proposed by Du (2013). Future research on sentiment transfer can be strengthened to seek a more robust method and validate findings.

The regression analysis results could have been affected by the cumulative positive herding effect in individual ratings of products. The sentiment score and star ratings were averaged for each restaurant to perform a regression analysis. Future studies may obtain a longer time series, use a larger range of data, add instrumental variables

(Lee *et al*., 2021), or perform a panel regression model for in-depth analysis of a larger regional scope. Finally, the Bag-of-words (BOW) approach has its limitations as well. It neglects the grammar effects of words and ignores their semantics. While BOW and LDA are widely used in text topic clustering, iterative methods are updated in the computing field every year to optimize accuracy. For this project, researchers opted to use two different clustering methods for better accuracy. Future researchers may use different approaches or clustering algorithms as they emerge continuously.

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