WHICEB 2022 Proceedings | Wuhan International Conference on e-Business

Summer 7-26-2022

Evaluating the Quality of Online Reviews based on Feature-richness

Kaiyu Liu
School of Information Management, Wuhan University, Wuhan, 430072, China; Center for E-commerce Research and Development, Wuhan University, Wuhan, 430072, China

Zhongyi Hu
School of Information Management, Wuhan University, Wuhan, 430072, China; Center for E-commerce Research and Development, Wuhan University, Wuhan, 430072, China, Zhongyi.hu@whu.edu.cn

Xiao Huang
School of Information Management, Wuhan University, Wuhan, 430072, China; Center for E-commerce Research and Development, Wuhan University, Wuhan, 430072, China

Jiang Wu
School of Information Management, Wuhan University, Wuhan, 430072, China; Center for E-commerce Research and Development, Wuhan University, Wuhan, 430072, China

Full Research Paper

Evaluating the Quality of Online Reviews based on Feature-richness

Kaiyu Liu, Zhongyi Hu[*]*, Xiao Huang, Jiang Wu*
School of Information Management, Wuhan University, Wuhan, 430072, China
Center for E-commerce Research and Development, Wuhan University, Wuhan, 430072, China

Abstract: Given the massive online reviews from online travel agencies, it is difficult for users to find high-quality reviews. Evaluating online reviews' quality has been an important matter of concern. In this study, a review quality assessment model based on feature richness was proposed by combining grounded theory and semantic similarity. The proposed model can properly evaluate the quality of online reviews from the perspective of feature richness, and the more comprehensive the review content, the higher the quality is. Based on the online review from ctrip.com, experimental results showed that the proposed model can accurately identify the reviews that contain rich information with a high reference value for other users.

Keywords: Online reviews, Review quality, Grounded theory, Semantic similarity

1. INTRODUCTION

With the popularization of Online Travel Agencies (OTA), online reviews have played a significant role in providing valuable information for travelers' decision-making. However, the number of reviews has been largely increased, making it far beyond the ability of users to read and process. Therefore, how to find the reviews that are useful to consumers from massive reviews is a matter of concern.

To help consumers quickly identify effective and high-quality reviews, many online platforms provide users with review filters based on the number of users' voting or rating which is regarded as a proxy of reviews' helpfulness. In the society of academia, various methods have also been proposed to evaluate the helpfulness of online reviews. For example, some studies have investigated the potential factors that influence the helpfulness of a review[1]; the Likert scale has also been applied to score the online reviews to measure their helpfulness[2]; the integrated econometrics and machine learning methods is another mainstream to predict the review's helpfulness based on the influencing factors of review helpfulness[3]. However, the users' voting or rating on reviews' helpfulness is usually under-estimated, because a review's voting is largely affected by many factors such as the review's date and place order.

This study proposed an unsupervised review quality estimation and ranking model. In this model, a review is regarded to be helpful if it contains rich information that readers concern. Specifically, we first extract important features through grounded theory based on online tourist reviews on ctrip.com. The featured words are used to as tourists' attention from the reviews. And then, PMI is applied to estimate reviews' feature richness, which is a criterion about whether the review text contains rich features and detailed descriptions.

2. LITERATURE REVIEW

To solve the problem of too many online reviews and redundant information, scholars have proposed a variety of quality assessment methods for online reviews to classify or filter reviews. Among those methods, evaluation methods based on the helpfulness of reviews are the most common. Review helpfulness can be used to measure review quality to a certain extent. The higher the review helpfulness, the greater the reference value to users, and the higher the review quality[4]. At present, there are two main methods for evaluating the helpfulness of reviews, econometric regression and supervised learning.

[*]Corresponding author. Email: Zhongyi.hu@whu.edu.cn (Zhongyi Hu)

Econometric regression is one of the most common methods used in review helpfulness research. Scholars took the helpfulness of the review votes as the evaluation index, and use the econometric regression model to study the important factors affecting the helpfulness of the review. Min et al.[5] mainly considered two types of influencing factors, one is the characteristics of the review itself, such as the degree of detail of the review, the semantics of the review, the time of the review, etc.; the other is the characteristics of the reviewer, including the reviewer's identity, professional degree, reliability, etc. Xiang et al.[6] compared three major foreign online travel websites, and explored the helpfulness factors of online reviews on different platforms. The results show that the linguistic features, semantic features, sentiment, and reviewer information of online reviews are different on different platforms and industries, and the impact on review helpfulness and review ratings varies widely. Shin et al.[7] studied the effects of hotel attributes, review length, and review readability on the review helpfulness using review ratings as moderating variables. The results show that review ratings moderated the impact of hotel attributes on review helpfulness. Different hotel attributes can have a positive impact on review helpfulness when matched with positive or negative reviews. Korfiatis et al.[8] analyzed the impact of review length and review readability on review helpfulness, and the results show that review readability had a greater impact on review helpfulness than review length. In addition, considering that there is an underestimation problem in online reviews, that is, there may be some or even a large number of readers who have read the reviews but did not vote[9], to solve this problem, some scholars have used TF-IDF, Word2Vec and cosine similarity to evaluate the helpfulness of other reviews based on the helpfulness of existing reviews[10,11].

The method of supervised learning is to take the review helpfulness as a classification problem, set review training sets through different classification standards, and use the extracted feature sets to test and evaluate the effect of classifiers, then find effective review features, so as to automatically identify high-quality reviews. Chen et al.[12] and Liu et al.[13] classified reviews into five categories according to their helpfulness (i.e. high quality, medium quality, low quality, duplicate, and spam), trained their classification models using manually annotated labels, and an effective information quality framework is adopted to extract representative review features. Zheng et al.[14] and Ghose et al.[3] classified reviews by setting a threshold of positive vote percentage (usually 60%), reviews with a percentage of positive votes above this threshold were considered helpful, and vice versa did not help. Ma and Li[15] proposed a review usefulness classification model by integrating multi-modal features, such as image semantic features, text vector embeddings.

To summarize, the existing studies mainly focused on investigating the influencing factors of review helpfulness or predicting whether reviews are useful, but few studies considered the review quality to evaluate the reviews’ helpfulness.

3. METHOD

This research aims to construct a review quality evaluation model based on feature richness by combining qualitative and quantitative methods. The model consists of three steps (see Figure 1): extraction of featured words, evaluation of feature richness, and review ranking. The grounded theory is used to qualitatively extract features, and then the feature richness is evaluated based on the Pointwise Mutual Information (PMI). Finally, the reviews are sorted in descending order according to the feature richness.

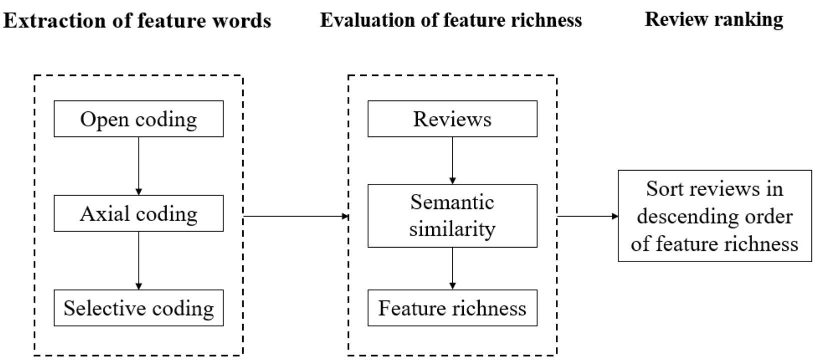

Figure 1. Quality assessment model based on feature-richness

3.1 Extraction of featured words

This paper used grounded theory to systematically code and summarize featured words from tourists' reviews. The Grounded theory is a qualitative research method that uses a systematic process for the inductive derivation of a phenomenon[16]. As a form of users' opinions, online reviews have become an important source of information for obtaining users' opinions in grounded theory[17,18]. In the absence of research on review quality ranking in the field of online tourism, this study chooses a more standardized programmatic grounded theory to encode and categorize the crawled online reviews, so as to extract featured words as important features of online reviews. The details of featured words extraction based on the grounded theory will be illustrated in section 4.2.

3.2 Evaluation of feature richness

We use PMI to evaluate the feature richness of online reviews. In the field of natural language processing, PMI is used to calculate the semantic similarity between two words. Its basic idea is to calculate the probability that two words appear at the same time in the text. The higher the probability, the more likely it is semantically related[19].

The procedure of feature richness calculation and ranking is showed in Figure 2. At first, each review will be processed by word segmentation and stop words removal, after which each review is represented by words set W_i. For each word, its semantic similarity with 19 selected featured words is calculated and then summed up, achieving an overall semantic similarity p_t. To limit the influence of the text length on the final score and avoid the phenomenon that a longer text has a higher score, the top 20 semantic similarities were used to calculate the feature richness $score_i$. That is, for each review, the PMI values of at most 20 words is accumulated to obtain the final score of the text, which is called feature richness. The richer of the review information, the greater the feature richness is. Finally, the reviews can be sorted by the value of feature richness.

Figure 2. Feature richness calculation and ranking model

```
Feature Richness Calculation and Ranking Model
input：reviews R={r1,…,rx}， featured words K={k1,…,k18}
for ri ∈R do
cut words and get Wi={w1,…,wm}
for wt ∈Wi do
pt ← ∑PMI(wt,kq), kq ∈K
end for
len ← length of ri
if len ≤ 100 then
    n ← [20 * len/100] + 1
```

else
  $n \leftarrow 20$
    take the first n words in descending order of p_t from W_i to form a set $S=\{s_1,\ldots,s_n\}$
score$_i \leftarrow \sum PMI(s_a,k_q)$, $s_a \in S$, $k_q \in K$
store score$_i$
end for
all reviews are sorted by score in descending order

output：final result

4. EXPERIMENTAL RESULTS

4.1 Data preparation

Review data were collected from Ctrip.com, which is one of the largest online travel agencies in China. In this study, a total of 24,487 review data were crawled. Reviews come from *Hongcun*, *Anren Ancient Town*, *Famen Temple*, *Hengdian*, *Huangguoshu Waterfall*, and other attractions in different types and styles. After segmenting the review text into words by the *Jieba* module in Python, we further filtered out function words, punctuation, symbolic expressions, high-frequency adjectives and modal particles based on the HIT's stop word expansion table.

4.2 Features extraction

4.2.1 Open coding

Open coding is the process of conceptualizing and defining the phenomena mentioned in online reviews. This is followed by mining the categories to be named, and finally using words or phrases to represent the essence of the reviews. We extracted 200 high-frequency words after word segmentation and removal of stop words. Words without actual or obvious meaning, such as "very" and "much", and nouns that are not universally representative such as "waterfall" and "town" were eliminated, and finally, 73 high-frequency words were remained. Table 1 lists the top 30 high-frequency words.

Table 1. High frequency words in user reviews (Top 30)

Ranking	Item	Frequency	Ranking	Item	Frequency	Ranking	Item	Frequency
1	view	7896	11	cost performance	1373	21	good looking	833
2	worth	6900	12	tickets	1363	22	like	788
3	spot	5014	13	beautiful	1202	23	service	763
4	experience	4782	14	time	1098	24	photograph	729
5	funny	3917	15	architecture	1080	25	hour	722
6	interesting	3152	16	scenery	1078	26	grand sight	671
7	attractions	2409	17	housing	931	27	hotel	657
8	feel	1577	18	performance	924	28	guide	657
9	play	1545	19	characteristic	916	29	tourist	646
10	convenient	1384	20	tour	904	30	eat	644

4.2.2 Axial coding

Axial coding refers to the process of discovering and establishing relationships between concepts and reducing data to a small set of topics or categories. At this stage, the similar concepts are grouped into the same conceptual label[20]. In this study, the main axial coding is performed on the 73 high-frequency words, and the high-frequency words with similar meanings are assigned to the same category to obtain secondary indicators.

4.2.3 Selective coding

Selective coding is the selection of core categories among the discovered conceptual categories and systematically linking them with other categories. This coding process involves identifying core categories[21] that represent major research themes, integrating categories derived from the open and axial coding process into a conceptual framework. In this phase of the analysis, the concepts and relationships revealed by the encoding process are compared with the existing literature. Based on to the traditional six elements of tourism, "food, accommodation, travel, shopping and entertainment" and related literature[22,23], the primary and secondary indicators obtained in this paper are shown in Table 2.

Table 2. Process of Online Review Feature Induction

Primary indicator	Secondary indicators	Keyword	Frequency
food and sup	food and sup	eat	644
accommodation	accommodation	housing	931
		hotel	657
		guesthouse	600
trip	traffic	traffic	430
		car	417
	time	time	1098
		hour	722
		in line	353
	together with	children	488
		friend	421
		together	358
tour	spot	spot	5014
		attractions	2409
		architecture	1080
	view	view	7896
		scenery	1078
	playability	play	1545
		tour	904
		playability	395
	ticket	ticket	1363
		fare	363
	service	service	763
		guide	657
		worker	355
		explain	348
shopping	commercialization	commercialization	560
		business	487
		buy	638
entertainment	performance	performance	924
		program	643
		show	421
	photograph	photograph	729

		photo	509
		shoot	417
	cultural deposits	history	511
		China	438
		culture	436
personal experience	cost performance	worth	6900
		cost performance	1373
	price level	expensive	503
		price	455
		free	330
	convenience	convenient	1384
	description of scenic spot features	beautiful	1202
		good-looking	833
		pretty	424
		funny	3917
		interesting	3152
		fantasy	419
		shocked	388
	description of experience	experience	4782
		feel	1577

For each secondary indicator, a core keyword is selected as the basis for the subsequent calculation of PMI values, that is, a total of 19 words shaded in Table 2. The keywords are selected generally based on the frequency of occurrence, and secondly consider the generality. For example, "together" can better identify users with other relatives and friends when traveling than "children" and "friends". “Culture” is more intuitive than "History" and "China" to reflect the cultural heritage of the scenic spot.

4.3 Feature richness calculation and ranking

According to the ranking model proposed in this paper, the score of each review is calculated, and the final ranking result is obtained by descending order. Table 3 only shows the partial ranking results of more than 20,000 review data. Take *Huangguoshu Waterfall* as an example.

The sorting algorithm in this paper considers the richness of information, and screen the high-quality review based on PMI-based feature-richness. Table 3 (a) shows the top 2 ranked reviews among thousands of reviews. As shown in the table, the top-ranked reviews have mentioned much more aspects, and gave specific information in details, rather than simply or generally evaluating good or bad. For example, the first review has covered at least five aspects, such as tickets, transportation, accommodation, attracted scenic spots, and food.

Table 3(a). The top 2 ranked reviews

Review ID	Review	Feature richness
14444	[About tickets] Current discounted fares: 40% off tickets for one-yard tour of Guizhou and sightseeing bus. If the 40% off tickets are sold out, you can buy 50% off tickets on other platforms, the fare is 140. Tips: 1. It is recommended to book tickets at least 3 days in advance. 2. The Huangguoshu Escalator needs to purchase additional tickets, or you can walk up and down. 3. Qingdao residents can enjoy 20% off the tickets. 4. Tickets are valid for 2 days, and the scenic spots that have been visited cannot be re-entered.	341.8969

	[About Transportation] 1. Take the high-speed rail to the north of Guiyang Anshun West, the fare is 46.5 yuan and the duration is about 30 minutes. There is a bus in Anshun West, which is said to be every hour, 22 yuan. Take the bus from Anshun Station to Anshun East Station to Huangguoshu Waterfall takes 22 yuan. 3. The shuttle bus for a day trip on the tourism platform is only responsible for your round-trip transportation, and you can play by yourself when you arrive at the scenic spot. This way I choose: Departure at 7:00 am to Huangguoshu at 9:00, return at 4:00 pm. [About accommodation] Originally planned to live in Anshun, because I didn't want to drag a suitcase there, I chose to go back and forth on the same day, and I can finish the game. [About the distribution of attractions] Huangguoshu The scenic spot includes three scenic spots, each of which is independent. There are shuttle buses between the scenic spots. The recommended tour sequence: Tianxing Bridge - Huangguoshu Waterfall – Doupotang. Tianxing Bridge: the most time-consuming and physically demanding. When I went here, the whole scenic spot is divided into the first half and the second half. There is basically nothing to see in the first half. It is good to walk quickly. The scenery is concentrated in the second half. Remember to go left and right at Gaolaozhuang. When you leave, you are out of the scenic spot. Generally, group tours only take you to the first half, and then tell you that there is nothing to see in the second half. Don't believe it! The most beautiful part of the second half is the Silver Chain Falling Pool Waterfall. I personally think that it is not inferior to Huangguoshu Waterfall. Huangguoshu Waterfall: the core scenic spot, unlike the Tianxing Bridge, there are many attractions along the way, there is only one Huangguoshu Waterfall. You can spend money to take the escalator, or you can walk up and down. The one-way escalator is 30 yuan, and the round-trip is 50 yuan. I walk the whole journey. If you only take one journey, it is recommended to take the escalator for the return journey. The Great Falls has 3 viewing platforms with good viewing angles. You can check in one by one. The Shuilian Cave will not be open when I go there. It is said that the opening time of the Shuilian Cave is very limited every year - Steep Pond is the smallest scenic spot. Someone introduced it before. Said that if there is not enough time, we can give up here. We hurry up and trot all the way and still check in here. This is the scene of the four masters and apprentices leading their horses across the river in the 86 version of Journey to the West. Although the Doupotang Waterfall is not as spectacular as the Huangguoshu Waterfall, it is wider than the Huangguoshu Waterfall. The food and beverage prices in the Huangguoshu scenic spot are quite conscientious. The corn is 10 yuan for 3, and the Liangpi is less than 15 a bowl. It is recommended to arrange 3-4 hours for Tianxing Bridge, 2-3 hours for Huangguoshu Waterfall, and 1 hour for Steep Pond.	
23910	The first time I come to Guizhou, the first stop must be the Huangguoshu Waterfall~ Now the scenic spot is in the off-season, although the weather is a bit cold, there are a lot fewer tourists, which is what I like. Hehe~ Huangguoshu Waterfall is the largest waterfall in China and Asia, has always been known for its vast water potential. Although its water flow in early winter is not as good as in summer, it is still very shocking, and the roar of the valley can be heard from far away. There are several viewing platforms near and far along the route, and the locationc are very good. It takes about 20 minutes to walk from the entrance to the waterfall. It takes about 20 minutes to go down the mountain. It is a bit tiring to go back up the mountain. You can also take the escalator, which costs 30 yuan one way or 50 yuan round trip. Doupotang Waterfall is the widest waterfall in the Huangguoshu Waterfall group. It is named after the water flows down the steep hillside. It is no less spectacular than the Huangguoshu Waterfall. This is still the original scene where the four of Tang Seng and his apprentice walked through the waterfall in the ending song of the 86 edition of Journey to the West. When you walk to the waterfall from the entrance, you will pass through beautiful woods and plank roads. There are several viewing platforms, and then the original road. Tianxingqiao has a typical karst landform, craggy rocks, and gurgling clear water surrounded	308.5545

	by it. The scenery is particularly beautiful, and it must be cool in summer. Divided into two sections, each section of the tour takes about 1.5-2 hours, depending on the individual's physical strength, only the first half of the tour or the entire journey. Counting steps has 365 stones with dates engraved on them, and you can find your birthday punch cards. In Journey to the West, Gao Laozhuang, where Zhu Bajie married his daughter-in-law, is also here, but it is now a shop selling souvenirs and food. Tickets for 160 yuan, shuttle bus for 50 yuan, off-season package ticket for 135 yuan (including scenic spot insurance). The winter is very cold, so be sure to keep warm. There are shuttle buses between each scenic spot in the scenic area. They are bundled together when you buy tickets. You must fasten your seat belts when riding. Wear comfortable clothes and shoes. For the first time, you need to swipe your ID card and facial recognition at the entrance. You don't need an ID card at the later attractions. You can directly swipe your face, which is very convenient.	

Table 3(b). The last 5 ranked reviews

Review ID	Review	Feature richness
19855	The experience is good and worth recommending.	-2.686
21010	It's a beautiful view.	-6.3355
11585	Nice! I like it!	-6.7773
18895	Worth recommending.	-7.7356
19596	Worth recommending.	-7.7356

Table 3(b) shows some of the lower-ranked reviews, which are characterized by mentioning very few specific aspects, or simply mentioning featured words but not describing details.

In summary, the ranking model in this paper has the following characteristics:

(1) Fully combine qualitative research methods with quantitative research methods. Extract important features by word frequency statistics, and use grounded theory to summarize and effectively represent the important aspects that users pay attention to when traveling;

(2) It can better distinguish high-quality or low-quality reviews from the perspective of information richness. It can be seen from Table 4 that the top-ranked reviews contain more specific features and detailed information, and have higher reference value for other users, while general and simple reviews get low scores and will be ranked at the back.

5. CONCLUSION

This study explored the quality assessment of online reviews and built a ranking model for users’ online reviews based on grounded theory and semantic similarity. Different from the traditional helpfulness-based evaluation, this paper used the qualitative research method of grounded theory in extracting important features. The constructed ranking model has achieved good results in empirical experiments, and can distinguish reviews that contain rich information and have high reference value for other users, and have certain practical value.

Overall, this research contributes in the following aspects:

(1) We propose an effective online review quality evaluation model for the online travel industry. The richer the information contained in the review, the more aspects involved, and the more specific the details mentioned, the more valuable it is for other users. Then the score will be correspondingly higher and the ranking will be higher. The ranking model proposed in this paper performs well in experiments and has certain practical value.

(2) In terms of research methods, different from traditional purely qualitative research or purely

quantitative research, this research adopts a combination of qualitative and quantitative research methods. When extracting important features, the grounded theory induction system is used to extract the parts that reviewers pay attention to, which not only obtains the important features of online reviews, but also systematically explains the main points that users pay more attention to tourism. After that, quantitative research methods are used to calculate the feature richness score of each review, and the quality of each review is presented intuitively as a score. In addition, the obtained featured words are universal in the online travel industry and can be used to calculate and sort online reviews of different scenic spots without re-exploring and summarizing user attention indicators for different scenic spots.

(3) It provides some ideas in the in-depth mining of online reviews. In the traditional online review quality assessment research, there is a problem that the content of the text itself is not sufficiently mined. Many studies only use linguistic features such as text length, review time, and reviewer identity to evaluate review quality. The ranking model proposed in this paper is based on aspects extraction and semantic similarity calculation. It deeply mines the review texts from the word level and considers the information richness of the text itself to find the key aspects that users pay attention to when traveling, so as to filter out valuable reviews.

In the future, the research will be improved from the following two perspectives.

(1) Further validation of the proposed model. The proposed model can be regarded as an unsupervised approach. To further validate the results of the proposed model, we will invite users to manually annotate the usefulness of reviews and examine the difference between annotated and calculated ranks.

(2) In the proposed model, the PMI value at the word level is used to estimate the semantic similarity. In the future, the extended SO-PMI (Semantic Orientation Pointwise Mutual Information) based model will be explored to consider the interaction of emotional tendencies.

ACKNOWLEDGEMENT

This research was supported by the National Key Research and Development Program of China under Grant 2019YFB1405600.

REFERENCE

[1] Fang, B., Ye, Q., Kucukusta, D., & Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. Tourism Management, 52: 498-506.

[2] Casaló, L. V., Flavián, C., Guinalíu, M., & Ekinci, Y. (2015). Avoiding the dark side of positive online consumer reviews: Enhancing reviews' usefulness for high risk-averse travelers. Journal of Business Research, 68(9): 1829-1835.

[3] Ghose, A., & Ipeirotis, P. G. (2010). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. IEEE transactions on knowledge and data engineering, 23(10): 1498-1512.

[4] Yang Ming, Qi Wei, Yan Xiangbin, Li Yijun. (2012). Research on utility analysis of online product reviews. Journal of Management Sciences in China, 15(05): 65-75. (in Chinese)

[5] Min Qingfei, Qin Liang, Zhang Keliang. (2017). Factor s affecting the preceives usefulness of online reviews. Management Review, 29(10): 95-107. (in Chinese)

[6] Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. Tourism Management, 58: 51-65.

[7] Shin, S., Du, Q., Ma, Y., Fan, W., & Xiang, Z. (2021). Moderating effects of rating on text and helpfulness in online hotel reviews: an analytical approach. Journal of Hospitality Marketing & Management, 30(2): 159-177.

[8] Korfiatis, N., García-Bariocanal, E., & Sánchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. Electronic Commerce Research and Applications, 11(3): 205-217.

[9] Guo, X., Chen, G., Wang, C., Wei, Q., & Zhang, Z. (2021). Calibration of Voting-Based Helpfulness Measurement for Online Reviews: An Iterative Bayesian Probability Approach. INFORMS Journal on Computing, 33(1): 246-261.

[10] Radev, D. R., Jing, H., Styś, M., & Tam, D. (2004). Centroid-based summarization of multiple documents. Information Processing & Management, 40(6): 919-938.

[11] Shi Da, Wang Lele, Yi Bowen. (2020). Deep data mining for online reviews usefulness: Hotel reviews data on TripAdvisor. Nankai Business Review, 23(05): 64-75, (in Chinese)

[12] Chen, C. C., & Tseng, Y.-D. (2011). Quality evaluation of product reviews using an information quality framework. Decision Support Systems, 50(4): 755-768.

[13] Liu, J., Cao, Y., Lin, C.-Y., Huang, Y., & Zhou, M. (2007). Low-quality product review detection in opinion summarization. Proceedings of the 2007 joint conference on empirical methods in natural language processing and computational natural language learning (EMNLP-CoNLL),

[14] Zheng, X., Zhu, S., & Lin, Z. (2013). Capturing the essence of word-of-mouth for social commerce: Assessing the quality of online e-commerce reviews by a semi-supervised approach. Decision Support Systems, 56: 211-222.

[15] Ma Chao, Li Gang, Chen Sijing, Mao Jin, Zhang Ji. (2020). Research on usefulness recognition of tourism online reviews based on multimodal data semantic fusion. Journal of the China Society for Scientific and Technical Information, 39(2): 199-207. (in Chinese)

[16] Glaser, B. G., Strauss, A. L., & Strutzel, E. (1968). The discovery of grounded theory; strategies for qualitative research. Nursing research, 17(4): 364.

[17] Sthapit, E., & Björk, P. (2019). Sources of distrust: Airbnb guests' perspectives. Tourism Management Perspectives, 31: 245-253.

[18] Liao Xiumei, Chen Yetian, Mi Chuanmin. (2019). Study on consumer satisfaction of Tangshan Hot Spring based on online reviews. Chinese Journal of Management Science, 27(7): 186-194, (in Chinese)

[19] Church, K., & Hanks, P. (1990). Word association norms, mutual information, and lexicography. Computational linguistics, 16(1): 22-29.

[20] Nunkoo, R., & Ramkissoon, H. (2016). Stakeholders' views of enclave tourism: A grounded theory approach. Journal of Hospitality & Tourism Research, 40(5): 557-558.

[21] Daengbuppha, J., Hemmington, N., & Wilkes, K. (2006). Using grounded theory to model visitor experiences at heritage sites: Methodological and practical issues. Qualitative Market Research: An International Journal.

[22] Lian Yi, Wang Xia. (2004). A case study and application of cunsumer satisfaction evaluation system in tourist destinations based and TDCSI. Tourism Tribune, 19(5): 9-13. (in Chinese)

[23] Dai Bin, Li Zhongguang, Tang Xiaoyun, Yang Honghao, He Qiongfeng. (2012). On the construction of tourist satisfaction evaluation system and its empirical study. Tourism Tribune, 27(07): 74-80. (in Chinese)