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An Online Hotel Selection Method With Three-Dimensional Analysis of Reviews' Helpfulness

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ABSTRACT

The multi-attribute decision-making method based on online reviews has been widely used in addressing the hotel selection problem. However, due to information overload and the presence of fake reviews, traditional hotel selection methods that rely solely on unverified review analysis can affect the outcome of hotel selections. In this study, a novel three-dimensional helpful review analysis model based multi-attribute decision-making approach for hotel selection is established. Firstly, a new three-dimensional helpful review analysis model that effectively filters out sentiment inconsistency reviews, topic inconsistency reviews, and reviews from invalid sources is proposed. Secondly, this study employs TF-IDF and LDA to extract attributes for hotel selection. We further utilize BERT to extract sentiment level for each attribute. Then, a ranking result for alternative hotels is obtained using a combination compromise solution method (CoCoSo). Finally, we demonstrate its effectiveness and feasibility through a case study of selecting the optimal hotel from TripAdvisor.com.

KEYWORDS

CoCoSo, Hotel Selection, Multi-Attribute Decision-Making, Online Reviews, Review Helpfulness, RFM

In recent years, with the popularization of new transportation tools, the time and material costs of people's travel have been reduced, which expands people's travel radius. The distance between the consumer and the destination makes it necessary to plan the travel well in advance, and it can be difficult to find a suitable hotel in time. Therefore, travel-reservation websites have become an important channel for consumers to understand and choose travel destinations, hotels, restaurants, and other travel-related products. Through the hotel-related information provided by the website, including photos, locations, and prices (Yu, 2024), consumers can obtain some level of knowledge about potential hotel choices. However, the specific details of the stay experience may need to be learned about through online reviews. Therefore, online reviews, which can provide consumers with multidirectional information about hotels, are playing an increasingly important role in hotel selection. Online reviews include many parts, such as review title, review content, and star rating. However, the explosive growth of online reviews has also produced some negative effects, such as information

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overload and the problem of fake reviews (Wang et al., 2020). Discovering how to identify helpful reviews and derive useful information from them is the key to solving the above problem. Existing studies have investigated online reviews from multiple perspectives. However, there are still some limitations, as follows.

The existing hotel-selection methods based on online reviews ignore the impact of online review helpfulness on decision-making (Wu et al., 2022; Qin et al., 2022). Hotel selection is a nonexpert decision, and online reviews can inform that purchase decision (Casalo et al., 2015; Qin et al., 2022; Wu et al., 2022). The existence of a large number of invalid reviews will affect the decision-making results and efficiency of consumers (Kauffmann et al., 2020; Song et al., 2023). Hotel selection based on helpful reviews can improve decision-making results and consumer satisfaction. Therefore, before online reviews are used to help consumers make decisions, it is necessary to analyze their helpfulness so that invalid reviews can be identified and excluded from influencing the final decision.

The helpfulness of reviews is usually analyzed from two aspects: textual features and non-textual features. Textual features mainly include sentiment analysis of the reviews as well as textual aspects. Most of the previous research on review helpfulness has analyzed the helpfulness of reviews in terms of textual features only while ignoring the impact of non-textual features. Non-textual features are an important part of online reviews (Siering et al., 2018; Liu & Park, 2015; Zhang et al., 2016), and most of the existing research has also demonstrated that non-textual features have an impact on review helpfulness. Therefore, it is necessary to choose a reasonable non-textual feature-analysis method.

To solve the above limitations, a new hotel-selection method with three-dimensional review-helpfulness analysis based on the helpfulness of reviews combined with the textual and non-textual characteristics of reviews is proposed to assist consumers in hotel selection. This method analyzes review helpfulness from review star sentiment consistency, review title content, text consistency, and key-user identification. The sentence-to-sentence attention network (S2SAN) method and the long short-term memory (LSTM) method are used to analyze the sentiment consistency and text consistency. The above two methods analyze review helpfulness in terms of textual features. Then the recency-frequency-monetary (RFM) model is utilized for key-user identification to analyze the review helpfulness from non-textual features. This can solve the problem of analyzing from only one side of the feature and lacking comprehensive consideration. At the same time, the RFM model also solves the problem of lack of theoretical basis in feature selection of non-textual features.

After the helpfulness of review analysis, a comprehensive weight method for combining subjective and objective weights is devised: 1) the objective weight is calculated using the term frequency–inverse document frequency (TF-IDF) model; 2) the subjective weight is obtained by the decision-making trial and evaluation laboratory (DEMATEL) method. The combined compromise solution (CoCoSo) method is utilized to calculate the final score of each hotel alternative to assist consumers to make decisions.

LITERATURE REVIEW

In the past few years, the impact of online-review helpfulness on hotel selection has received extensive attention from researchers. This section provides a brief literature review focusing on hotel-selection methods based on online reviews and review helpfulness.

Hotel-Selection Methods Based on Online Reviews

As hotel selection is typically a nonexpert decision, online reviews can provide information for the purchase decision. Therefore, hotel selection based on online-review information has attracted the attention of some scholars.

For example, Sharma et al. (2019) studied the sentiment polarity of hotel-evaluation attributes in reviews and sorted hotels by combining the subsets to help consumers make choices. Peng et al. (2018) thought that the existing model is not enough to cope with the massive amount of online information and ignored the influence of the internal connection of different attributes on consumer decision-making. They proposed a new hotel-decision support model, which uses a probabilistic linguistic term set (PLTS) to statistically summarize online-review information. Combined with probabilistic linguistic integrated cloud, online reviews are further processed, and hotel ranking results are output through a hotel-selection model.

Nie et al. (2020) constructed a new semantic segmentation sentiment dictionary and conducted sentiment analysis on online reviews through this dictionary; then they built a decision matrix to get hotel rankings. Mishra et al. (2023) examined the factors that influence the impact of online reviews and found that the perception of usefulness and the factors influencing customers' views on online evaluations play a significant role in determining the helpfulness of the review process. Chang et al. (2023) constructed a Kansei-related dictionary toward hotel domain by Kansei text-mining from online reviews; then a group hotel ranking based on group affective preference was interactively generated to meet the personalized group demands.

Qiu et al. (2024) proposed a hybrid method based on BERT and TF-IDF and extracted the evaluation attributes of bed and breakfasts from Airbnb's online reviews. Ji et al. (2023) identified user needs by analyzing online reviews, which in turn assisted the group in completing hotel selection based on the preferences of various subgroups of the group. Li et al. (2005, 2009) developed multi-criteria decision-making methods with linguistic variables and uncertainty information; based on this, Yu et al. (2018) proposed a multi-criteria decision-making method with fuzzy linguistic distribution based on online reviews.

From the existing research results, it can be found that the research focus is on sentiment analysis of online reviews and hotel feature extraction (Zhang et al., 2022; Tsai et al., 2020; Usama et al., 2020). These studies do not consider the helpfulness filtering of online reviews as the source of data. In fact, online platforms contain a large amount of invalid data, including false data, which will affect the selection results and then mislead consumers into making wrong decisions.

Review Helpfulness

In the decision-making problem, review helpfulness is actually a measure of the perceived value of the information contained in reviews in the decision-making process (Siering et al., 2018). But fake reviews can't provide helpful information. They are designed to influence consumers' opinions or behavior by making untrue claims or defamatory statements about a product or service. Therefore, for users who need to decide which hotel is appropriate for their trip, fake and unreliable reviews can mislead them into making wrong decisions, rendering these reviews unhelpful. Conversely, real and reliable reviews can assist users in their hotel-selection decisions. Hence, helpful reviews should not only eliminate false reviews but also exclude unreliable ones. The helpfulness of online reviews is analyzed below in terms of both textual and non-textual features.

Some scholars have studied the review helpfulness from text features. For example, Mitra and Jenamani (2021) considered the degree of influence of semantic and syntactic features of reviews on the review helpfulness and obtained the influence weights of each feature on the helpfulness of reviews under different datasets through empirical research and analysis. Zhou et al. (2020) analyzed the online review data and found that the similarity between the review title and the review text has a positive impact on the helpfulness of the review. Chatterjee (2020) analyzed the impact of emotional intensity in reviews on the helpfulness of reviews. Zheng et al. (2021) identified unreliable consumer reviews with biased ratings by predicting review scores from review texts and comparing them with ratings given by consumers. Compared with existing studies, this method analyzes both textual consistency and sentiment consistency, which can eliminate some fake reviews with inconsistent titles and contents as well as inconsistent sentiments. However, it is not enough to analyze the review helpfulness only from the text features; the reviewer is also an important factor affecting the review helpfulness.

Other scholars have analyzed the review helpfulness from the perspective of non-textual features. For example, Siering et al. (2018) analyzed review helpfulness in conjunction with the consideration of reviewer-related factors and found experimentally that reviewer-related factors produced a greater impact than review-text factors. Liu and Park (2015) considered the openness of the reviewer's information as well as the reputation of the reviewer in their study of review helpfulness and found that both factors had a positive impact on review helpfulness. For non-textual features, most of the existing studies considered the relevant features of reviewers (Javed et al., 2021; Malik, 2020), but there was no systematic study on the relationship between features. As a mature key-user mining model in marketing, the RFM model has a certain theoretical basis. Cheng and Chen (2009) and Sarvari et al. (2016) have verified the effectiveness of this model, but there is no research on the application of RFM in the identification of review sources for review-helpfulness analysis.

To sum up, the above research analyzes the characteristics of hotel-selection problems based on online reviews and proposes feasible decision-making methods, but there are still two major problems:

- Review helpfulness: the existence of a large number of invalid reviews will affect the decision-making results and efficiency of consumers. Hotel selection based on helpful reviews can improve the accuracy of decision-making results and consumer satisfaction.
- Non-textual feature-selection problem: the combination of non-textual features without theoretical basis has different degrees of relevance and contradiction, which is difficult to deal with in the decision-making process.

Therefore, based on the helpfulness of reviews, this paper proposes a new hotel-selection method with three-dimensional review-helpfulness analysis, combining the textual and non-textual features of reviews, to assist consumers in hotel selection. In terms of textual features, reviews are analyzed from the perspective of star rating and sentiment consistency of reviews, as well as the textual consistency of review titles and content; in the aspect of non-textual features, the RFM model is used to identify the reviewers so as to comprehensively consider the helpfulness of the reviews. The helpful reviews obtained after screening are used for multi-attribute decision-making to help consumers select hotels.

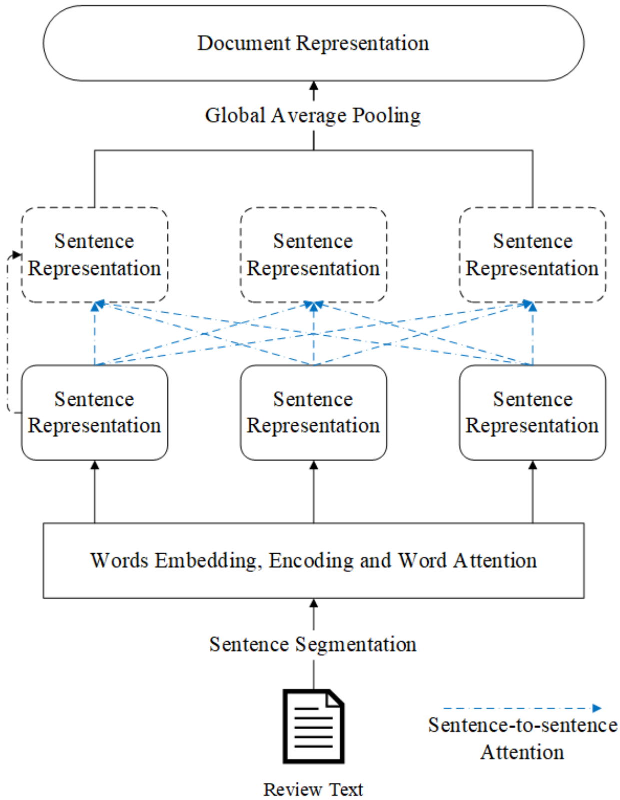
PRELIMINARIES

The Sentence-to-Sentence Attention Neural Network Method

Consumers' online reviews usually include feelings about the purchased goods or services. Analyzing the emotion included in consumer reviews is a problem to be solved in the existing research on online reviews. Attention-based neural networks have achieved remarkable results in some natural language processing tasks (Usama et al., 2020). The attention mechanism is a human simulation that assigns more weight to useful information (Min et al., 2020). Unlike traditional text, the online review is a highly colloquial text and does not necessarily have the sequential relationship between sentences as in traditional text (Fu et al., 2020). Therefore, attention-based neural networks can be used for sentiment analysis of online reviews. Existing research still focuses mainly on word-level attention. Although some studies have further considered sentence-level attention, sentence-level attention in these studies was also derived by calculating word-level attention. Calculating word-level attention usually takes into account the sequential relationship between words, and there is no obvious sequential relationship between sentences in reviews. Therefore, calculating sentence-level attention by analogy in a word-level way may add unnecessary complexity.

S2SAN (Wang et al., 2021) is the sentiment-classification model based on a sentence-to-sentence attention neural network, which uses self-attention instead to build a hierarchical attention framework. Generally, for word aspect, BI-GRU-ATT is used for encoding in S2SAN. For sentence aspect, self-attention is used to encode. Then it obtains a document representation. The hierarchical attention network (HAN) mechanism (Cheng et al., 2017) is a deep-learning model for processing textual data that automatically learns and attends to important information in the input text. The model performs

Figure 1. Sentence Attention in S2SAN (Wang et al., 2021)



well in processing text data with hierarchical structure. Compared to HAN, the accuracy of the model is improved by 1.2% and the training time is reduced by 25%. The sentence-to-sentence attention in the model is shown in Fig. 1.

The specific calculation steps are as follows.

Step 1: Use GRU units to encode the words.

After input embedding, GRU units are used to encode the words in the sentence and input them to the attention layer for attention calculation, and the output of the attention layer is the sentence representation. The hierarchy of review r is shown by (1):

$$\mathrm{r} = \begin{bmatrix} s_1 \\ \dots \\ s_M \end{bmatrix} = \begin{bmatrix} v_1^1, v_2^1, \dots, v_N^1 \\ \dots \\ v_1^M, v_2^M, \dots, v_N^M \end{bmatrix} \in R^{M \cdot N \cdot d} \tag{1}$$

where M is the total number of sentences in the review, N is the number of words in each sentence, and d is the dimension of each word vector.

Step 2: Obtain the word representation model h_n^m.

After computing the semantic representation of the review $\mathrm{r} \in R^{M \cdot N \cdot d}$, the word representation model h_n^m is obtained by inputting $v_n^m \in R^d$ into the forward GRU unit $\vec{\mathrm{h}}_n^m$ and the backward GRU unit $\overleftarrow{\mathrm{h}}_n^m$.

$$\vec{\mathrm{h}}_n^m = \overrightarrow{GRU}\left(v_n^m, \vec{\mathrm{h}}_{n-1}^m\right) \tag{2}$$

$$\overleftarrow{\mathrm{h}}_n^m = \overrightarrow{GRU}\left(v_n^m, \overleftarrow{\mathrm{h}}_{n+1}^m\right) \tag{3}$$

$$\mathrm{h}_n^m = \left[\vec{\mathrm{h}}_n^m, \overleftarrow{\mathrm{h}}_n^m\right] \tag{4}$$

Step 3: Calculate the word attention weight α_n^m.

In sentence *m*, the attentional weight of word *n* is computed by (5) and (6).

$$u_n^m = tanh\left(W_w h_n^m + b_w\right) \tag{5}$$

$$\alpha_n^m = softmax\left(u_w \cdot u_n^{m\mathrm{T}}\right) \tag{6}$$

where α_n^m represents the attention weight calculated by word *n* in sentence *m*, u_n^m is the word-level context, and W_w and b_w are the weight matrix and the bias, respectively.

Step 4: Calculate sentence attention vector weights.

Multiply and sum the hidden output of each word h_n^m with the attention weight α_n^m to get the attention weight vector for the whole sentence in (7):

$$v_s = \sum_{i=1}^{|S|} \alpha_n^m \cdot h_n^m \tag{7}$$

where v_s represents the sum of attention of all words in sentence *S*, α_n^m represents the attention weight of word *n* in sentence *m*, and $|S|$ represents the length of the sentence sequence *S*.

Step 5: Scaled dot-product attention is used to calculate attention.

$$Attention\left(Q,K,V\right) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right)V \tag{8}$$

where $Q = K = V = \left(v_{s1}, v_{s2}, \ldots, v_{sn}\right)^T$ is a copy of the sentence representation. $\sqrt{d_k}$ is a constant that has a supervisory effect to prevent the inner product from becoming too large; d_k is usually set to 64.

Step 6: The final document representation is then obtained through a global homogenization pool operation. Finally, the document representation vector is fed into a softmax classifier to predict the sentiment polarity of review r.

The LSTM Method

LSTM is a mature recurrent neural network model that has many applications in natural language processing. In the existing research, some scholars have used the LSTM model to analyze semantic similarity. Based on the structural characteristics of LSTM itself, the similarity of two sentences of different lengths can be compared. Based on the LSTM model, the Manhattan LSTM (Mueller & Thyagarajan, 2016) model processes one text in the sample pair through two LSTM networks with shared weights. The model uses Manhattan distance as a new metric, and the experimental results are better than Euclidean distance and cosine similarity. With Manhattan distance, complex semantics can be modeled using simple LSTM models.

The RFM Method

The RFM model is a well-established model in marketing that is designed to analyze users from three main indicators, namely recency, frequency, and monetary. In the traditional RFM model (Sarvari et al., 2016; Wang et al., 2021), recency represents the time interval between the customer's last purchase and the current one, frequency represents the number of purchases made by the customer in a certain period, and monetary represents the total monetary value of purchases made by the customer in a certain period. According to different application scenarios, the definition of three indicators in the RFM model needs to be adjusted as follows.

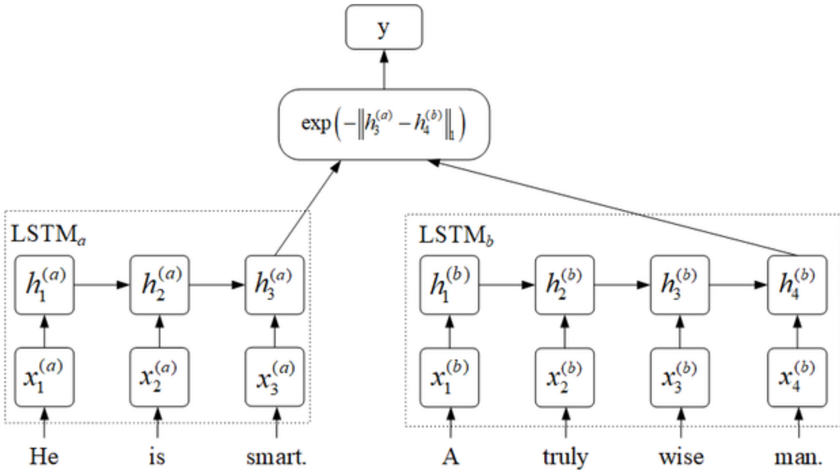
Recency

Recency represents the time (the unit is day) since the reviewer last posted an online review of the hotel. In $R_i = N - d_i$, R_i denotes recency, N denotes deadline, and d_i represents the last time a review was posted. In order to eliminate the influence of different attribute units of measurement in the RFM model, it is necessary to normalize the data, as shown in (9):

$$R_i^* = 1 - \frac{R_i - R_{min}}{R_{max} - R_{min}} \tag{9}$$

where R_{max} denotes the maximum recency of all reviewers and R_{min} represents the minimum recency of all reviewers.

Figure 2. Manhattan LSTM Model



Frequency

Frequency indicates the number of times a reviewer has posted an online review of a hotel in a certain period, as shown in (10):

$$F_i^* = \frac{F_i - F_{min}}{F_{max} - F_{min}} \tag{10}$$

where F_{max} denotes the maximum frequency of all reviewers and F_{min} represents the minimum frequency of all reviewers.

Monetary

Monetary represents the total monetary value spent by consumers in a certain period. Here, the sum of average hotel prices is used as an alternative and the unit is RMB, as shown in (11):

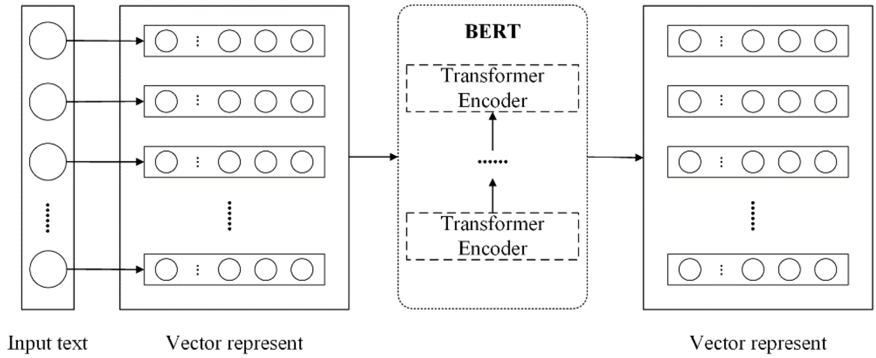
$$M_i^* = \frac{M_i - M_{min}}{M_{max} - M_{min}} \tag{11}$$

where M_{max} denotes the maximum monetary of all reviewers and M_{min} represents the minimum monetary of all reviewers.

The Bidirectional Encoder Representations from Transformers (BERT) Method

Bidirectional Encoder Representations from Transformers (BERT) is a pre-training model based on a bidirectional Transformer (Zhao & Yu, 2021). Its sentence-level feature-extraction capability based on word vectors is excellent, and due to the characteristics of its internal Transformer self-attention module, it has better “memory” ability in long-distance dependence problems. In the aspect of sentiment analysis, the BERT model can be analyzed by splicing sentences and attributing words together into BERT. This method can effectively capture attribute-based emotions in sentences and is robust against overfitting.

Figure 3. The BERT Model



The Probabilistic Linguistic Term Set

PLTS is a concept based on fuzzy-set theory, which has the advantage of describing emotional information, uncertainty, and fuzziness comprehensively and in detail (Zhang et al., 2014).

Definition 1 (Liu et al., 2018): Let be a linguistic-term set where $L^{(k)}\left(p^{(k)}\right)$ represents the linguistic term $L^{(k)}$ associated with the probability $p^{(k)}$ and $\# L\left(p\right)$ represents the number of language-term sets contained in the probabilistic language-term set $L\left(p\right)$. Then the PLTS method is used to express the emotion score and probability density of the reviews. For example, if *S* is a linguistic evaluation set, $S = \left\{s_0 : negative, s_1 : neutral, s_2 : positive\right\}$; in a hotel-review set, if 30% of consumers give a negative evaluation, 40% give a neutral evaluation, and 30% give a positive evaluation, then the information can be expressed as $L_{1(p)} = \left\{s_0\left(0.3\right), s_1\left(0.4\right),\ s_2\left(0.3\right)\right\}$. The attribute value of this information is $c = s_0 \times 0.3 + s_1 \times 0.4 + s_2 \times 0.3$.

The DEMATEL Technique

The DEMATEL technique is a method used to capture complex relationships and interactions among a large number of attributes, and it is easy to propose the most important attributes that affect other attributes without a lot of information (Govindan et al., 2015). By observing the degree of pair-to-pair interaction between attributes, this method uses a matrix and related mathematical theories to calculate the structural relationship and influence intensity between attributes and establishes a system model between attributes (Tzeng et al., 2007).

Step 1: Establish the direct-influence matrix $A = \left[a_{ij}\right]_{m\times n}$, where a_{ij} represents the direct impact of attributes i on attributes j. The degree of impact is divided into four levels from 0 to 3, where 0 means no impact, 1 means moderate impact, 2 means strong impact, and 3 means very strong impact.

Step 2: Normalize the direct-influence matrix A and obtain the direct-influence matrix X.

$$X = k \times A$$

$$k = \frac{1}{max\sum_{i=1}^{n} a_{ij}} 1 \le i \le n \tag{12}$$

Step 3: Calculate the synthesizing-influence matrix T.

$$T = X(I - X)^{-1} \tag{13}$$

Step 4: Calculate the sums of rows and columns of synthesizing-influence matrix T. The sum of rows and sum of columns are represented by vectors R and C, which can be computed by:

$$R = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = \left[t_i\right]_{n\times 1}, i = 1,2,\ldots,n \tag{14}$$

$$C = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} = \left[t_j\right]_{1\times n}, j = 1,2,\ldots,n \tag{15}$$

Step 5: Calculate the weights for each attribute, as shown in (16) and (17):

$$\eta_j = \sqrt{\left(R_j + C_j\right)^2 + \left(R_j - C_j\right)^2}, j = 1,2,\ldots,n \tag{16}$$

$$\omega_j = \frac{\eta_j}{\sum_{j=1}^{n} \eta_j}, j = 1,2,\ldots,n \tag{17}$$

where R_j represents the j^{th} element of the vector R and C_j does the same. η_j represents the importance of the j^{th} criterion; ω_j then represents the weight of the j^{th} criterion.

The CoCoSo Method

Multi-attribute decision-making methods have been widely used to solve the hotel-selection problem (Li et al., 2007a, 2007b). The CoCoSo method (Yazdani et al., 2019) is a decision method based on combination perspective and compromise perspective that can effectively deal with multi-attribute decision problems and take into account the mutual influence and weight between different attributes. Specifically, when dealing with decision-making problems, the CoCoSo method can simultaneously take into account the preferences of decision-makers and the importance of various attributes so as to make the final decision result more objective and comprehensive. In addition, the CoCoSo method has high computational efficiency and ease of use and is suitable for various types of decision problems. Therefore, in practical applications, the CoCoSo method has a wide range of application prospects and practical value.

The CoCoSo method is as follows:

Step 1: Determine the initial decision matrix R.

$$R = \left(r_{ij}\right)_{m\times n} \tag{18}$$

where r_{ij} denotes the evaluation value given by the expert for each alternative AL_i based on the j^{th} attribute.

Step 2: Obtain the standardized decision matrix $\tilde{R} = \left(\tilde{r}_{ij}\right)_{m \times n}$.

$$\tilde{R} = \left(\tilde{r}_{ij}\right)_{m \times n} = \begin{cases} \tilde{r}_{ij} = r_{ij}, for \;\; benefit \;\; attribute \\ \tilde{r}_{ij} = -r_{ij}, for \;\; cost \;\; attribute \end{cases} \tag{19}$$

Step 3: Calculate the arithmetic weighted sum $S(AL_i)$ of each alternative AL_i.

$$S\left(AL_i\right) = \sum\nolimits_{j=1}^{m} w_j \tilde{r}_{ij}, i = 1,2,3,\ldots,m \tag{20}$$

Step 4: Calculate the geometric weighted sum $P(AL_i)$ of each alternative AL_i.

$$P\left(AL_i\right) = \sum\nolimits_{j=1}^{m} \left(w_j\right)^{\tilde{r}_{ij}}, i = 1,2,3,\ldots,m \tag{21}$$

Step 5: Calculate the relative importance of alternative AL_i, as shown in (22) to (24).

$$Ka\left(AL_i\right) = \frac{P\left(AL_i\right) + S\left(AL_i\right)}{\sum\nolimits_{i=1}^{m}\left(P\left(AL_i\right) + S\left(AL_i\right)\right)}, i = 1,2,\cdots,m \tag{22}$$

$$Kb\left(AL_i\right) = \frac{P\left(AL_i\right)}{minP\left(AL_i\right)} + \frac{S\left(AL_i\right)}{minS\left(AL_i\right)}, i = 1,2,\cdots,m \tag{23}$$

$$Kc\left(AL_i\right) = \frac{\lambda P\left(AL_i\right) + \left(1-\lambda\right)S\left(AL_i\right)}{\lambda maxlimits_i P\left(AL_i\right) + \left(1-\lambda\right) maxlimits_i S\left(AL_i\right)}, i = 1,2,\cdots,m \tag{24}$$

Step 6: Calculate the score AL_i for each alternative AL_i, as shown in (25).

$$K\left(AL_i\right) = \sqrt[3]{Ka\left(AL_i\right)Kb\left(AL_i\right)Kc\left(AL_i\right)} + \frac{1}{3}\left(Ka\left(AL_i\right) + Kb\left(AL_i\right) + Kc\left(AL_i\right)\right) \tag{25}$$

ANALYSIS

Due to the helpfulness of massive online-review data, a new hotel-selection method based on online reviews is proposed and applied to online hotel selection. Online reviews are analyzed for helpfulness in terms of review text consistency, sentiment consistency, and key-user identification. Through analysis of the information contained in helpful reviews, a multi-attribute decision-making approach is used to help consumers make decisions. Existing studies on the helpfulness of reviews include mainly textual features and non-textual features.

The Three-Dimensional Review-Helpfulness Analysis

Sentiment Consistency Analysis of Reviews

The review helpfulness is studied from the perspective of text features. Online reviews given by consumers are the expression of consumers' emotional tendency toward satisfaction after experiencing the service of a hotel, and review star rating is the quantitative expression of consumers' emotional tendency toward hotel satisfaction. Therefore, the consistency between the review sentiment and the star rating is an important indicator to measure the helpfulness of reviews (Al-Natour & Turetken, 2020). The S2SAN model is used to analyze the sentiment of the review, and the consistency analysis is performed with the sentiment expressed by the star rating of the review. Reviews that pass the sentiment consistency analysis enter the next step.

Text Consistency Analysis of Reviews

From the perspective of linguistic meaning, the review title is a generalization of the review content, so the semantics of the review title should be similar to or the same as the semantics of the review content. Therefore, the consistency between the review title and the review content is also an important indicator to judge the helpfulness of the review (Zhang et al., 2016). The LSTM model is used to analyze the text consistency of reviews and content consistent with sentiment analysis and retain consistent reviews.

Key-User Identification

The review helpfulness is studied from the perspective of non-textual features, and the RFM model is used to identify the key users of the reviewers. Then the reviews posted by the key users are matched. Key-user identification is performed by RFM model for the writers of the reviews retained after the above two consistency analyses, as shown in (26). The reviews made by these key users are identified as true reviews.

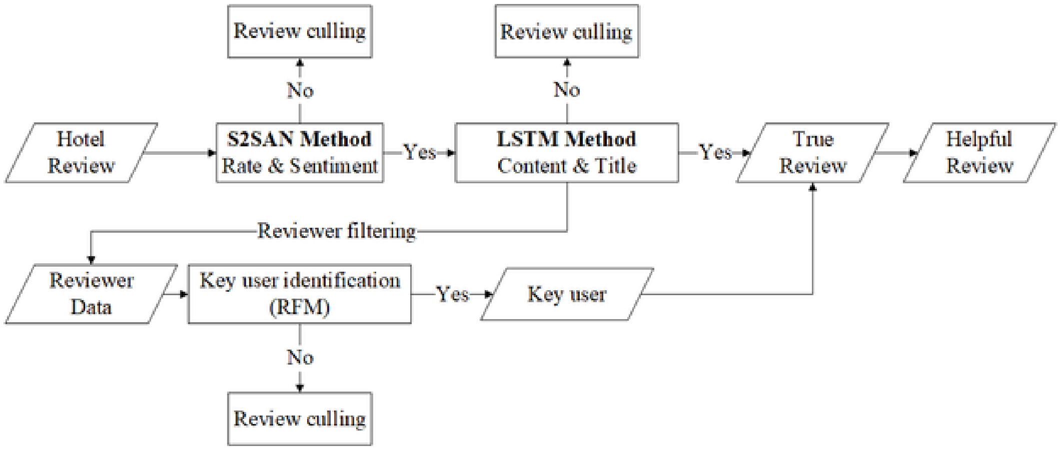
$$RFM = R + F + M \tag{26}$$

The Hotel-Selection Method

After getting helpful reviews, attribute extraction, attribute emotion polarity annotation, and subjective and objective attribute weight calculation are carried out on the reviews after the above analysis, and hotel selection is based on attribute scores of the hotels. The method of combining TF-IDF and latent Dirichlet allocation (LDA) is used to obtain attribute words by processing online-review data.

TF-IDF assigns a weight to each word by calculating how often it occurs in the document (TF) and how often it occurs in the whole corpus (IDF). TF refers to word frequency, which indicates how often a word appears in a document. It is calculated as the number of times a word appears in a document divided by the total number of words in the document, and the results are usually normalized to prevent longer documents from having higher word frequencies.

Figure 4. Helpful-Review Filtering Process



$$TF_{ij} = \frac{n_{ij}}{\sum_k n_{kj}} \tag{27}$$

where n_{ij} represents the frequency of the occurrence of t_i in text d_j.

IDF refers to inverse document frequency and is used to measure the general importance of a word. It is calculated as the total number of documents divided by the logarithm of the number of documents containing the word.

$$IDF_i = \log \frac{|D|}{\left|\left\{j : t_i \in d_j\right\} + 1\right|} \tag{28}$$

where $|D|$ represents the total number of all texts and $\left\{j : t_i \in d_j\right\}$ represents the number of texts containing the word t_i in the text.

Multiply TF with IDF to get the importance score (TF-IDF) of a word in a document. If a word occurs frequently in the current document but rarely in the whole document set, it will have a high TF-IDF value, indicating that the word is important for the current document.

$$TF - IDF_{ij} = TF_{ij} \times IDF_i \tag{29}$$

In this way, each document can be represented as a vector where each element represents the weight of a word. LDA is a topic model, which can discover potential topics from document collection (Xie et al., 2020; Guo et al., 2017). The LDA model is used to fit the TF-IDF vectorized review data. After fitting, the number of topics and topic words can be extracted from the LDA model.

The BERT method is used to label the sentiment polarity of attribute words in online reviews. After that, the sentiment value of each attribute is calculated by PLTS. Combined with the objective weight value of the TF-IDF attribute and the subjective weight value of consumers for each attribute obtained by the DEMATEL method, the attribute value of the candidate hotel is calculated. According to the obtained attribute values, the CoCoSo method is used to calculate the score values of each alternative hotel to obtain the ranking results.

In summary, considering the existence of invalid reviews, a new approach is proposed to filter out unhelpful reviews using S2SAN, LSTM, and RFM models and make decisions using helpful reviews combined with a multi-attribute approach. First, the review is obtained from the online platform. Second, the review helpfulness is analyzed by S2SAN, LSTM, and RFM. Third, by performing attribute extraction (TF-IDF and LDA) for helpful reviews and emotion tagging (BERT) for each attribute in the reviews, the objective weights (TF-IDF and LDA) and subjective weights (DEMATEL) of the attributes are combined to get the comprehensive weights. Finally, the final results are obtained using the CoCoSo method. Fig. 5 shows the flowchart of the proposed method. The process is specified as the following steps.

Step 1: Analyze the sentiment of reviews using the S2SAN model, and analyze that sentiment for consistency with the sentiment indicated by the star ratings. Retain sentiment-consistent reviews.
Step 2: For reviews that have been retained through Step 1, use the LSTM model to analyze the text consistency of review titles and review content. Retain textually consistent reviews.
Step 3: Identify key users' reviews using the RFM model by (9) to (11) and (26). In the reviews through Step 2, retain the reviews posted by the key users. The algorithm for Step 1 to Step 3 is shown in Algorithm 1 below.
Step 4: Extract the attribute words in the reviews using a method that combines the TF-IDF model and the LDA model and obtain the objective weights of each attribute word.
Step 5: Perform the emotion tag of each attribute in the review using the BERT model and calculate the attribute value of each attribute using the PLTS method.
Step 6: Calculate the subjective weights of each attribute using the DEMATEL method by (12) through (17) and calculate the combined weights of each attribute by combining the objective weights obtained in Step 4.
Step 7: Calculate the score for each alternative hotel by (18) through (25).
Step 8: Select the optimal supplier rank by the CoCoSo method.

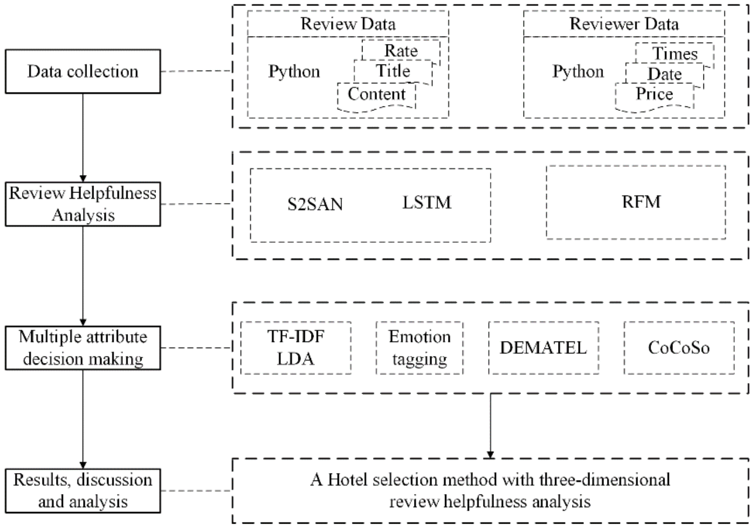
CASE STUDY

With the improvement of people's living standards and the increase of leisure time, more and more people choose to travel. As a key part of travel, hotel choice has become particularly important. At the same time, the hotel industry is also facing challenges such as increasing market competition and diversified customer needs, and it must provide more transparent and personalized services through online platforms. Online booking platforms provide consumers with a wealth of hotel information and convenient booking services, making consumers more and more inclined to search and compare through the internet to more easily find hotels that meet their needs. However, in online hotel reviews, the existence of a large number of invalid reviews will affect the decision-making results and efficiency of consumers. Therefore, the hotel-selection method based on three-dimensional review-helpfulness analysis proposed in this paper can improve the accuracy of decision-making results so that people can choose hotels that better meet their needs, increasing consumer satisfaction.

Data Collection

The ranking problem of five hotels in New York is used as a case study. The data came from Tripadvisor, an international travel website. The five hotels that were selected are The New Yorker, A Wyndham Hotel (x_1), New York Marriott Marquis (x_2), Hyatt Grand Central New York (x_3),

Figure 5. Flow Chart of the Hotel-Selection Method With Three-Dimensional Review Helpfulness Analysis



Algorithm 1. Three-Dimensional Review Helpfulness Analysis

Input: Origin Online Hotel Reviews Set $OR = \{or_1, or_2, or_3, \ldots, or_m\}$, where m means the number of reviews in the origin reviews set; Reviewers Set $RW = \{rw_1, rw_2, rw_3, \ldots, rw_k\}$, where *k* means the number of reviewers in the reviewer set

Output: Helpful Online Hotel Reviews Set $HR = \{hr_1, hr_2, hr_3, \ldots, hr_n\}$, where n means the number of reviews in the helpful review set

1: **for** origin online hotel review or_l in OR

2: Using S2SAN model to Identify Sentiment Polarity of Reviews, meanwhile translating star ratings into emotional polarity

3: **if** S2SAN model sentiment analysis result = the sentiment polarity of star ratings

Return filtered review fr_t

else :

Exclude review or_l

Obtain Filtered Reviews Set $FR = \{fr_1, fr_2, fr_3, \ldots, fr_t\}$

4: **for** each filtered review fr_t

5: Using LSTM model to analysis review text and title text consistency

if LSTM model analysis result = True

continued on following page

Algorithm 1. Continued

Return true review tr_i

else :

Exclude filtered review fr_t

Obtain True Reviews Set TR $= \{tr_1, tr_2, tr_3, \ldots, tr_i\}$

6: **for** reviewer rw_k in RW

7: Using RFM model to obtain reviewer's RFM values

8: **if** reviewer's RFM value ≥ 0.5

Return key user $kuser_j$

else :

Exclude reviewer rw_k

Obtain Key Users Set $KUser = \{kuser_1, kuser_2, kuser_3, \ldots, kuser_j\}$

9: **for** reviewers of true review tr_i

if reviewer of true review tr_i is key user

Return helpful review hr_n

else :

Exclude true review tr_i

Obtain Helpful Reviews Set $HR = \{hr_1, hr_2, hr_3, \ldots, hr_n\}$

Hotel Edison (x_4), and Hotel Midtown (x_5). The 50,527 online reviews of the five candidate hotels and the relevant information of reviewers were crawled using Python.

Case Results and Analysis

Review-Helpfulness Analysis

First, the experimental review data were input into the consistency analysis of review star rating and review sentiment, the sentiment polarity of the review was predicted using the S2SAN method, and then the results predicted by S2SAN were matched with the sentiment polarity expressed by the review rating. In the experiment, 5,637 reviews with inconsistent star rating and review sentiment were removed and 44,890 reviews were retained. Some of the results are shown in Table 1.

Second, the remaining 44,890 reviews were preprocessed, which mainly included four steps: 1) remove stop words; 2) convert uppercase to lowercase; 3) remove punctuation; 4) perform word segmentation.

The preprocessed data was input into the LSTM model for a new analysis of the text consistency between the review title and the review content. In the experiment, a total of 22,218 reviews with

Figure 6. Tripadvisor Reviews Sample

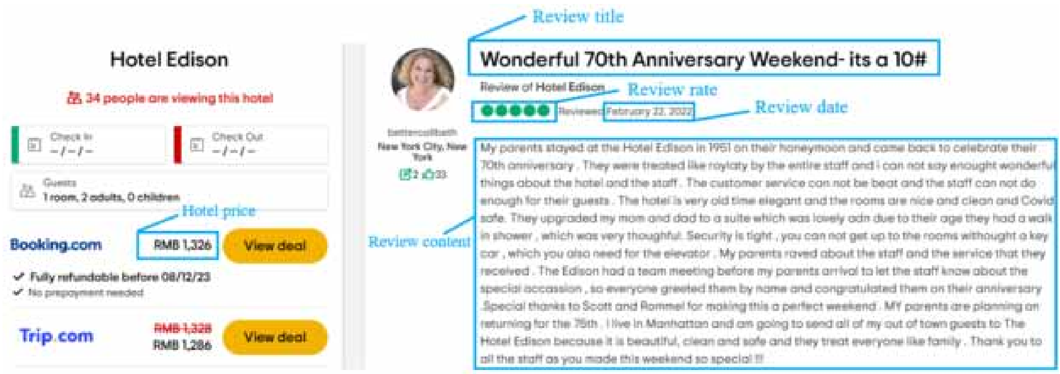


Table 1. Results of Consistency Analysis of Review Rating and Review Sentiment

Review Rating	Review Sentiment	Review Content	Negative Probability	Neutral Probability	Positive Probability	Consistent (Y/N)
2	Negative	We had read...	0.345	0.353	0.302	N
1	Negative	I have just...	0.503	0.475	0.022	Y
3	Neutral	Time has...	0.025	0.552	0.423	Y
4	Positive	If you only...	0.003	0.283	0.713	Y
5	Positive	My flight out...	0.0141	0.117	0.870	Y

inconsistent text titles and review content were identified, and 22,672 reviews were retained. Some of the results are shown in Table 2.

Third, based on the relevant information of reviewers in the experimental review data obtained previously, the hotel consumption of each reviewer from 2018 to now was analyzed from three indicators, recency, frequency, and monetary, using the RFM model. The RFM threshold was set to 0.5, and 8,091 key reviewers were identified by consensus. Some of the results are shown in Table 3.

Finally, the reviewers of the previously reserved 22,672 reviews were matched with the list of key reviewers, and 10,292 reviews published by key reviewers were identified. In summary, the filtering of helpful reviews was completed and a total of 10,292 helpful reviews were obtained. Some of the results are shown in Table 4.

Hotels Ranking

A combination of the TF-IDF and LDA methods extracted 10 attributes from all the original reviews and helpful reviews, respectively. Analyzing the extracted attribute words and the attribute revealed that part of the attribute words and the attribute do not have a subordinate relationship. The meaning of the word with the highest weight in each topic and the logical relationship between the attribute words are considered to name the attribute (Zhang et al., 2016b, 2022). Six representative attributes related to hotel reviews were identified and named: food (c_1), clean (c_2), price (c_3), location (c_4), service (c_5), and room (c_6). Each attribute of the helpful reviews is shown in Table 5, and the top

Table 2. Results of Text Consistency Analysis Between Review Title and Review Content

Review Title	Review Content	Consistent Prediction (1/0)	Consistent (Y/N)
Disappointing	The Hilton…	1	Y
Fabulous hotel	Great location…	0	N
No bueno	This hotel...	1	Y
Not to…	As ap…	0	N
Really hoping…	So far…	0	N

Table 3. Key-User Identification Results

Reviewer	Recency	Frequency	Monetary	RFM Value	Key User (Y/N)
traveroo	0.068	0	0.007	0.074	N
311natashaf	0.649	0.043	0.064	0.757	Y
AKent55	0.572	0.014	0.006	0.593	Y
binky78c	0.365	0.043	0.017	0.426	N
121paulineh	0.063	0	0.002	0.065	N

Table 4. Review-Helpfulness Filtering Results

Review Rating	Review Title	Review Content	Reviewer	S2SAN	LSTM	RFM	Helpful Review (Y/N)
1	Bad service	Staff don't know what they should do...	acastellaneta	Y	Y	N	N
5	Best Bartender in NYC	My family and I came to the Bridges Bar ...	Laurmichkell	Y	Y	Y	Y

Table 5. Helpful-Review Attribute Word

Attribute	Word 1	Weight 1	Word 2	Weight 2	Word 3	Weight 3	Word 4	Weight 4
Food	restaurant	102.162	coffee	86.526	breakfast	0	bar	0
Clean	clean	169.808	/	/	/	/	/	/
Price	price	93.862	fee	82.001	charge	0	pay	0
Location	times square	610.529	location	456.249	view	201.564	station	126.580
Service	staff	246.793	check	130.747	service	112.784	front desk	59.761
Room	room	884.237	bathroom	135.988	bed	129.414	shower	105.724

four words with weight values were selected for each attribute representation due to space limitations. The weight value of each attribute word under each attribute was summed up to obtain the objective weight value of each attribute and normalized, as shown in Table 6.

On this basis, the six attributes identified were used as evaluation indicators for ranking the alternative hotels. The DEMATEL method was used to obtain the subjective weight of each attribute.

Table 6. Helpful-Review Attribute Objective Weight Value

Attribute	Food	Clean	Price	Location	Service	Room
ω_o	0.053	0.048	0.050	0.387	0.132	0.330

First, the initial matrix A of DEMATEL was obtained, as shown in Table 7, and then the subjective weight values of each attribute were obtained according to the steps of the DEMATEL method, as shown in Table 8.

After the subjective weight value and objective weight value of each attribute were obtained, the comprehensive weight value of each attribute $\omega_o = \left\{\omega_1,\ldots,\omega_6\right\}$ was obtained by taking the arithmetic average of the subjective and objective weight value, as shown in Table 9.

After that, the BERT method was used to annotate the emotion of each attribute in each review on the helpful-review dataset and the original-review dataset. Positive sentiment was marked as 5, neutral sentiment was marked as 3, and negative sentiment was marked as 1, corresponding to the 5-point scoring system of the website. The values of each attribute of the hotel $c_o = \left\{c_1,\ldots,c_6\right\}$ were calculated according to the PLTS method, as shown in Table 10.

The attribute-value matrix is also the hotel-attribute decision matrix. After obtaining the hotel-attribute decision matrix and the comprehensive weight of each attribute, the candidate hotels were ranked by the CoCoSo method. The result of ranking the alternative hotels according to the CoCoSo method was $x_2 \succ x_5 \succ x_4 \succ x_1 \succ x_3$.

To illustrate the impact of helpful-review filtering on the outcome of consumer hotel purchase decisions, this study compared the objective weight values of attributes obtained from the unfiltered original dataset and the final ranking results. From the original unfiltered review dataset, which contained a total of 50,527 online reviews, the objective weight values of attributes were obtained by the TF-IDF and LDA methods as follows. The objective weight values in Table 11 were combined with the subjective weight values in Table 8 to obtain the comprehensive weight values of the original dataset.

Table 7. DEMATEL Initial Matrix

	Food	Clean	Price	Location	Service	Room
Food	0	2	2	2	1	0
Clean	3	0	2	1	0	3
Price	1	1	0	3	1	2
Location	0	3	2	0	0	1
Service	2	0	1	2	0	0
Room	0	2	1	1	0	0

Table 8. Attribute Subjective Weight Value

Attribute	Food	Clean	Price	Location	Service	Room
ω_s	0.053	0.048	0.050	0.387	0.132	0.330

Table 9. Helpful-Review Attribute Comprehensive Weight Value

Attribute	Food (ω_1)	Clean (ω_2)	Price (ω_3)	Location (ω_4)	Service (ω_5)	Room (ω_6)
ω_i	0.108	0.130	0.121	0.287	0.115	0.238

Table 10. Helpful-Review Attribute Value

	c_1	c_2	c_3	c_4	c_5	c_6
x_1	3.069	3.179	2.913	3.254	3.144	3.117
x_2	3.209	3.185	2.947	3.380	3.212	3.336
x_3	3.033	3.078	2.812	3.261	3.002	3.126
x_4	3.086	3.177	2.934	3.238	3.182	3.164
x_5	3.053	3.165	2.850	3.368	3.130	3.150

Table 11. Original Review Attribute Objective Weight Value

Attribute	Food	Clean	Price	Location	Service	Room
ω_o	0.072	0.025	0.041	0.314	0.173	0.374

After the sentiment value obtained by the BERT method, the value of each attribute of the hotel in the original review set was calculated according to the PLTS method.

The result of ranking under the original review set obtained by ranking the alternative hotels by the CoCoSo method was $x_2 \succ x_1 \succ x_5 \succ x_4 \succ x_3$.

The ranking of attribute weights of the original dataset obtained from Table 12 was compared with the ranking of attribute weights obtained from helpful-review filtering. At the same time, the ranking of decision results of the original dataset obtained from Table 13 was compared with the ranking of decision results obtained from helpful-review filtering, and the results are shown in Table 14.

CONCLUSION

This paper presents a hotel-selection method with a three-dimensional review helpfulness analysis and uses the ranking problem of five hotels in New York City as an example. In this method, the helpful reviews are first filtered by performing review star rating and review sentiment consistency analysis (S2SAN), review text and review content text consistency analysis (LSTM), and key-user identification (RFM) on the reviews. Then the reviews are analyzed to extract the attribute words, the TF-IDF weight is used as the objective weight, and the subjective weight is calculated. Furthermore,

Table 12. Original Review Attribute Comprehensive Weight Value

Attribute	Food $\left(\omega_1\right)$	Clean $\left(\omega_2\right)$	Price $\left(\omega_3\right)$	Location $\left(\omega_4\right)$	Service $\left(\omega_5\right)$	Room $\left(\omega_6\right)$
ω_i	0.118	0.119	0.117	0.250	0.136	0.160

Table 13. Original Review Attribute Value

	c_1	c_2	c_3	c_4	c_5	c_6
x_1	3.069	3.175	2.910	3.314	3.165	3.123
x_2	3.206	3.191	2.947	3.445	3.252	3.356
x_3	3.003	3.071	2.778	3.279	2.956	3.067
x_4	3.069	3.145	2.925	3.247	3.147	3.131
x_5	3.017	3.111	2.812	3.271	3.039	3.097

Table 14. Comparison Result

	Helpful Review	Original Review
Attribute Importance Ranking	$\omega_{o4} \succ \omega_{o6} \succ \omega_{o5} \succ \omega_{o1} \succ \omega_{o3} \succ \omega_{o2}$	$\omega_{o6} \succ \omega_{o4} \succ \omega_{o5} \succ \omega_{o1} \succ \omega_{o3} \succ \omega_{o2}$
Hotel Ranking	$x_2 \succ x_5 \succ x_4 \succ x_1 \succ x_3$	$x_2 \succ x_1 \succ x_5 \succ x_4 \succ x_3$

the comprehensive weights are obtained by combining the subjective and objective weights. On this basis, the best ranking results of the alternative hotels are obtained based on the CoCoSo method. The results show that there are differences in the objective weight ranking of attributes and the ranking results of hotels between the processed helpful reviews and the initial reviews without processing. This shows that helpful-review filtering is indeed useful in the hotel-ranking problem.

At the same time, there are still some shortcomings in this paper. First, due to the problem of data availability, this paper collects data from only the Tripadvisor platform; data from other websites can be used for further verification. Second, it considers the hotel-ranking problem for only a single consumer; in the future, we can consider the group decision-making problem (Xing et al., 2024) in the group travel situation.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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REFERENCES

Al-Natour, S., & Turetken, O. (2020). A comparative assessment of sentiment analysis and star ratings for consumer reviews. *International Journal of Information Management*, *54*, 102132. doi:10.1016/j.ijinfomgt.2020.102132

Casaló, L. V., Flavián, C., Guinalíu, M., & Ekinci, Y. (2015). Do online hotel rating schemes influence booking behaviors? *International Journal of Hospitality Management*, *49*, 28–36. doi:10.1016/j.ijhm.2015.05.005

Chang, J. L., Li, H., & Wu, J. (2023). How tourist group books hotels meeting the majority affective expectations: A group selection frame with Kansei text mining and consensus coordinating. *Group Decision and Negotiation*, *32*, 327–358. doi:10.1007/s10726-022-09810-0

Chatterjee, S. (2020). Drivers of helpfulness of online hotel reviews: A sentiment and emotion mining approach. *International Journal of Hospitality Management*, *85*, 102356. doi:10.1016/j.ijhm.2019.102356

Cheng, C.-H., & Chen, Y.-S. (2009). Classifying the segmentation of customer value via RFM model and RS theory. *Expert Systems with Applications*, *36*(3), 4176–4184. doi:10.1016/j.eswa.2008.04.003

Cheng, J., Zhao, S., Zhang, J., King, I., Zhang, X., & Wang, H. (2017). Aspect-level sentiment classification with HEAT (HiErarchical ATtention) network. In *CIKM '17: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (pp. 97–106). ACM. doi:10.1145/3132847.3133037

Fu, X., Ouyang, T., Chen, J., & Luo, X. (2020). Listening to the investors: A novel framework for online lending default prediction using deep learning neural networks. *Information Processing & Management*, *57*(4), 102236. doi:10.1016/j.ipm.2020.102236

Govindan, K., Khodaverdi, R., & Vafadarnikjoo, A. (2015). Intuitionistic fuzzy based DEMATEL method for developing green practices and performances in a green supply chain. *Expert Systems with Applications*, *42*(20), 7207–7220. doi:10.1016/j.eswa.2015.04.030

Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent Dirichlet allocation. *Tourism Management*, *59*, 467–483. doi:10.1016/j.tourman.2016.09.009

Javed, M. S., Majeed, H., Mujtaba, H., & Beg, M. O. (2021). Fake reviews classification using deep learning ensemble of shallow convolutions. *Journal of Computational Social Science*, *4*(2), 883–902. doi:10.1007/s42001-021-00114-y

Ji, F., Cao, Q., Li, H., Fujita, H., Liang, C., & Wu, J. (2023). An online reviews-driven large-scale group decision making approach for evaluating user satisfaction of sharing accommodation. *Expert Systems with Applications*, *213*, 118875. doi:10.1016/j.eswa.2022.118875

Kauffmann, E., Peral, J., Gil, D., Ferrández, A., Sellers, R., & Mora, H. (2020). A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making. *Industrial Marketing Management*, *90*, 523–537. doi:10.1016/j.indmarman.2019.08.003

Li, D. F. (2005). An approach to fuzzy multiattribute decision making under uncertainty. *Information Sciences*, *169*(1–2), 97–112. doi:10.1016/j.ins.2003.12.007

Li, D. F. (2009). Multiattribute group decision making method using extended linguistic variables. *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems*, *17*(6), 793–806. doi:10.1142/S0218488509006273

Li, D. F., & Sun, T. (2007a). Fuzzy linear programming approach to multi-attribute decision-making with linguistic variables and incomplete information. *Advances in Complex Systems*, *10*(4), 505–525. doi:10.1142/S0219525907001306

Li, D. F., & Sun, T. (2007b). Fuzzy LINMAP method for multiattribute group decision making with linguistic variables and incomplete information. *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems*, *15*(2), 153–173. doi:10.1142/S0218488507004509

Liu, D., Chen, X., & Peng, D. (2018). Distance measures for hesitant fuzzy linguistic sets and their applications in multiple criteria decision making. *International Journal of Fuzzy Systems*, *20*(7), 2111–2121. doi:10.1007/s40815-018-0460-0

Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management*, *47*, 140–151. doi:10.1016/j.tourman.2014.09.020

Malik, M. S. I. (2020). Predicting users' review helpfulness: The role of significant review and reviewer characteristics. *Soft Computing*, *24*(18), 13913–13928. doi:10.1007/s00500-020-04767-1

Min, X., Zhai, G., Zhou, J., Zhang, X.-P., Yang, X., & Guan, X. (2020). A multimodal saliency model for videos with high audio-visual correspondence. *IEEE Transactions on Image Processing*, *29*, 3805–3819. doi:10.1109/TIP.2020.2966082 PMID:31976898

Mishra, A., Kishan, K., & Tewari, V. (2023). The influence of online reviews on consumer decision-making in the hotel industry. *Journal of Data Acquisition and Processing*, *38*(3), 2559–2573.

Mitra, S., & Jenamani, M. (2021). Helpfulness of online consumer reviews: A multi-perspective approach. *Information Processing & Management*, *58*(3), 102538. doi:10.1016/j.ipm.2021.102538

Mueller, J., & Thyagarajan, A. (2016). Siamese recurrent architectures for learning sentence similarity. In *Proceedings of the AAAI Conference on Artificial Intelligence,* Vol. 30*, No. 1*. AAAI Press. doi:10.1609/aaai.v30i1.10350

Nie, R.-X., Tian, Z.-P., Wang, J.-Q., & Chin, K. S. (2020). Hotel selection driven by online textual reviews: Applying a semantic partitioned sentiment dictionary and evidence theory. *International Journal of Hospitality Management*, *88*, 102495. doi:10.1016/j.ijhm.2020.102495

Peng, H.-G., Zhang, H.-Y., & Wang, J.-Q. (2018). Cloud decision support model for selecting hotels on Tripadvisor.com with probabilistic linguistic information. *International Journal of Hospitality Management*, *68*, 124–138. https://doi.org/https://doi.org/10.1016/j.ijhm.2017.10.001. doi:10.1016/j.ijhm.2017.10.001

Qin, J., Zheng, P., & Wang, X. (2022a). Comprehensive helpfulness of online reviews: A dynamic strategy for ranking reviews by intrinsic and extrinsic helpfulness. *Decision Support Systems*, *163*, 113859. doi:10.1016/j.dss.2022.113859

Qin, Y., Wang, X., & Xu, Z. (2022b). Ranking tourist attractions through online reviews: A novel method with intuitionistic and hesitant fuzzy information based on sentiment analysis. *International Journal of Fuzzy Systems*, *24*(2), 755–777. doi:10.1007/s40815-021-01131-9

Qiu, D., Wang, C., & Xie, J. (2024). A novel TODIM-based multi-attribute decision making method under information described by Z-numbers for selecting online B&B. *Information Sciences*, *663*, 120315. doi:10.1016/j.ins.2024.120315

Sarvari, P. A., Ustundag, A., & Takci, H. (2016). Performance evaluation of different customer segmentation approaches based on RFM and demographics analysis. *Kybernetes*, *45*(7), 1129–1157. doi:10.1108/K-07-2015-0180

Sharma, H., Tandon, A., Kapur, P. K., & Aggarwal, A. G. (2019). Ranking hotels using aspect ratings based sentiment classification and interval-valued neutrosophic TOPSIS. *International Journal of System Assurance Engineering and Management*, *10*(5), 973–983. doi:10.1007/s13198-019-00827-4

Siering, M., Muntermann, J., & Rajagopalan, B. (2018). Explaining and predicting online review helpfulness: The role of content and reviewer-related signals. *Decision Support Systems*, *108*, 1–12. doi:10.1016/j.dss.2018.01.004

Song, Y., Wang, L., Zhang, Z., & Hikkerova, L. (2023). Do fake reviews promote consumers' purchase intention? *Journal of Business Research*, *164*, 113971. doi:10.1016/j.jbusres.2023.113971

Tsai, C.-F., Chen, K., Hu, Y.-H., & Chen, W.-K. (2020). Improving text summarization of online hotel reviews with review helpfulness and sentiment. *Tourism Management*, *80*, 104122. doi:10.1016/j.tourman.2020.104122

Tzeng, G.-H., Chiang, C.-H., & Li, C.-W. (2007). Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert Systems with Applications*, *32*(4), 1028–1044. doi:10.1016/j.eswa.2006.02.004

Usama, M., Ahmad, B., Song, E., Hossain, M. S., Alrashoud, M., & Muhammad, G. (2020). Attention-based sentiment analysis using convolutional and recurrent neural network. *Future Generation Computer Systems*, *113*, 571–578. doi:10.1016/j.future.2020.07.022

Wang, L., Wang, X.-K., Peng, J.-J., & Wang, J.-Q. (2020). The differences in hotel selection among various types of travellers: A comparative analysis with a useful bounded rationality behavioural decision support model. *Tourism Management*, *76*, 103961. doi:10.1016/j.tourman.2019.103961

Wang, P., Li, J., & Hou, J. (2021). S2SAN: A sentence-to-sentence attention network for sentiment analysis of online reviews. *Decision Support Systems*, *149*, 113603. doi:10.1016/j.dss.2021.113603

Wu, J., Hong, Q., Cao, M., Liu, Y., & Fujita, H. (2022a). A group consensus-based travel destination evaluation method with online reviews. *Applied Intelligence*, *52*(2), 1306–1324. doi:10.1007/s10489-021-02410-6

Wu, J., Liu, C., Wu, Y., Cao, M., & Liu, Y. (2022b). A novel hotel selection decision support model based on the online reviews from opinion leaders by best worst method. *International Journal of Computational Intelligence Systems*, *15*(1), 19. doi:10.1007/s44196-022-00073-w

Xie, Q., Zhang, X., Ding, Y., & Song, M. (2020). Monolingual and multilingual topic analysis using LDA and BERT embeddings. *Journal of Informetrics*, *14*(3), 101055. doi:10.1016/j.joi.2020.101055

Xing, Y., Wu, J., Chiclana, F., Liang, C., & Yager, R. R. (2024). An incentive mechanism-based minimum adjustment consensus model under dynamic trust relationship. *IEEE Transactions on Cybernetics*, 1–13. Advance online publication. doi:10.1109/TCYB.2023.3349257 PMID:38261505

Yazdani, M., Zaraté, P., Kazimieras Zavadskas, E., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision*, *57*(9), 2501–2519. doi:10.1108/MD-05-2017-0458

Yu, G. F. (2024). A multi-objective decision method for the network security situation grade assessment under multi-source information. *Information Fusion*, *102*, 102066. doi:10.1016/j.inffus.2023.102066

Yu, S. M., Wang, J., Wang, J. Q., & Li, L. (2018). A multi-criteria decision-making model for hotel selection with linguistic distribution assessments. *Applied Soft Computing*, *67*, 741–755. doi:10.1016/j.asoc.2017.08.009

Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016a). What online reviewer behaviors really matter? Effects of verbal and nonverbal behaviors on detection of fake online reviews. *Journal of Management Information Systems*, *33*(2), 456–481. doi:10.1080/07421222.2016.1205907

Zhang, G., Dong, Y., & Xu, Y. (2014). Consistency and consensus measures for linguistic preference relations based on distribution assessments. *Information Fusion*, *17*, 46–55. doi:10.1016/j.inffus.2012.01.006

Zhang, Z., Guo, J., Zhang, H., Zhou, L., & Wang, M. (2022). Product selection based on sentiment analysis of online reviews: An intuitionistic fuzzy TODIM method. *Complex & Intelligent Systems*, *8*(4), 3349–3362. doi:10.1007/s40747-022-00678-w

Zhang, Z., Zhang, Z., & Yang, Y. (2016b). The power of expert identity: How website-recognized expert reviews influence travelers' online rating behavior. *Tourism Management*, *55*, 15–24. doi:10.1016/j.tourman.2016.01.004

Zhao, A., & Yu, Y. (2021). Knowledge-enabled BERT for aspect-based sentiment analysis. *Knowledge-Based Systems*, *227*, 107220. doi:10.1016/j.knosys.2021.107220

Zheng, T., Wu, F., Law, R., Qiu, Q., & Wu, R. (2021). Identifying unreliable online hospitality reviews with biased user-given ratings: A deep learning forecasting approach. *International Journal of Hospitality Management*, *92*, 102658. doi:10.1016/j.ijhm.2020.102658

Zhou, Y., Yang, S., Li, Y., Chen, Y., Yao, J., & Qazi, A. (2020). Does the review deserve more helpfulness when its title resembles the content? Locating helpful reviews by text mining. *Information Processing & Management*, *57*(2), 102179. doi:10.1016/j.ipm.2019.102179

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