IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 27, 2020, accepted December 8, 2020, date of publication December 14, 2020, date of current version December 30, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3044252

Revealing Customer Satisfaction With Hotels Through Multi-Site Online Reviews: A Method Based on the Evidence Theory

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This work was supported in part by the Humanities and Social Science Foundation of Ministry of Education of China under Project 19YJA630037, in part by the Scientific Research Project of Liaoning Provincial Department of Education under Project LQN201922, in part by the Public Security Theory and Soft Science Foundation of Ministry of Public Security of China under Project 2018LLYJXJXY054, and in part by the Liaoning Planning Foundation of Social Science under Project L17AGL001 and Project L18BGL016.

ABSTRACT Hotel managers can learn about hotel customer satisfaction by analyzing online reviews. There are differences in the experience of reviewers, the release time and the degree of recognition for different online reviews, which leads to different reliability in reflecting customer satisfaction. The issue of how to determine hotel customer satisfaction more rationally with this reliability in mind is still a problem. To address this problem, this paper proposes a method for measuring hotel customer satisfaction based on the Dempster-Shafer (D-S) evidence theory, which considers the reliability of online reviews and information from multiple online travel review websites. This method is composed of three stages. First, considering the difference in online reviews' reliability, the basic probability assignment is generated based on online reviews. Next, the aggregation of the evaluation information is conducted based on the entropy weight method and Dempster's rule of combination. Finally, the utility function is used to calculate the expected utility, and customer satisfaction is analyzed based on the calculated expected utility. Therefore, improvement strategies of customer satisfaction can be developed according to customer satisfaction ranking. To verify the feasibility and effectiveness of this method, a case study for four hotels is presented. The proposed method is expected to help hotel managers understand the hotel's customer satisfaction, and develop corresponding improvement strategies to enhance its competitiveness.

INDEX TERMS Customer satisfaction, hotel, online reviews, reliability, Dempster-Shafer evidence theory, the entropy weight method.

I. INTRODUCTION

Customer satisfaction is a key concept in services marketing and management [1]–[4]. Especially in the hotel industry, customer satisfaction is not only directly related to the image [5] and performance [6] of the hotel but also the key to the long-term success of the hotel operation [7]. High customer satisfaction can improve customer loyalty and hotel's customer retention rate [8], [9], and it helps existing customers recommend the hotel to potential customers. In this way, customer satisfaction can increase the number of customers and drive increases in profitability, thereby improving hotel's performance [6], [10].

There are many related theories of customer satisfaction. Previous literature indicates that the expectancy-disconfirmation theory, equity theory, attribution theory, dissonance theory and contrast theory are commonly used in customer satisfaction research [11], [12]. Among them, the most frequently applied is the expectancy-disconfirmation theory [13]. Before purchasing a certain product or service, the customer will have performance expectation regarding the product or service, and then compare the actual perception with the expectation after purchasing. If the actual performance is better than the expectation,

The associate editor coordinating the review of this manuscript and approving it for publication was Zeshui Xu.

positive disconfirmation will occur; if the actual performance is equal to the expectation, no disconfirmation will occur; if the actual performance is lower than the expectation, negative disconfirmation will occur. Among them, no disconfirmation and positive disconfirmation cause customer satisfaction, whereas negative disconfirmation leads to customer dissatisfaction. When applying this theory in researching customer satisfaction, some methods can be used to inquire directly about the extent to which customer's service experience exceeded, met, or fell short of expectation. In existing research, the methods for obtaining the degree of expectation disconfirmation include questionnaires [14] and interviews [14]–[16], among other methods. However, the relevant information obtained from the customer through these ways may not truly reflect the satisfaction of the customer after the stay, due to the customer's reluctance to cooperate or the interference of other external factors in the investigation process.

With the widespread application of Internet technology, customers are more likely to book hotels online; after staying, some customers post reviews on the booking website concerning their stay. The evaluation information reflects the extent to which the customer's service experience exceeds, meets, or falls short of expectation. Additionally, potential customers will refer to these reviews before booking hotels. Therefore, compared with data obtained by questionnaires, interviews, or other ways, online reviews are generated spontaneously by customers, which can better reflect the customer's real satisfaction with the hotel and be of practical significance. In addition, the openness of the Internet also makes this way of data acquisition more cost-effective. The existing studies on hotel evaluation based on online reviews are mainly classified into three aspects. (1) Studies on the influence factors of hotel customer satisfaction based on online reviews. For instance, Xiang *et al.* analyzed online textual reviews collected from Expedia.com to deconstruct customer experience and explore the relationship between customer experience and customer satisfaction [17]. Radojevic *et al.* used a multilevel analytical framework to analyze customer satisfaction from five levels: service encounter, visitor, visitor's nationality, hotel, and destination. They found that the most powerful influence factors were hotel attributes and visitor characteristics [18]. Mariani *et al.* conjointly analyzed the influence of hotel service attributes and reviewers' cultural background on the customer satisfaction on the basis of online reviews and revealed the positive and negative factors of hotel customer satisfaction [19]. Liu *et al.* explored the difference in customer satisfaction determinants among different language groups and found that Chinese tourists preferred room-related hotel attributes [20]. Xu *et al.* used latent semantic analysis (LSA) and the regression analysis method to investigate the driving factors of customer satisfaction and dissatisfaction [21]. Guo *et al.* extracted the dimensions of hotel customer satisfaction from textual reviews using latent Dirichlet allocation (LDA) and further identified the most important dimensions by perceptual mapping [22]. (2) Studies on hotel selection based on online reviews. For instance, Peng *et al.* developed a hotel decision support model based on online reviews, where probabilistic linguistic term sets were used to sum evaluation information up [23]. Liang *et al.* proposed a quantitative method for hotel selection. In the method, textual reviews were transformed into distribution linguistic information by using feature extraction and sentiment analysis, and a new distribution linguistic VIKOR (DL-VIKOR) decision model was developed for ranking hotels [24]. Nie *et al.* established a semantic partitioned sentiment dictionary for determining the sentiment level of textual reviews, and proposed a hotel selection model based on the evidence theory in the context of LDAs [25]. To explore the differences in hotel selection among different types of travelers, Wang *et al.* used TF-IDF and Word2Vec algorithms to obtain the key factors and the criterion importance, and proposed a picture fuzzy TODIM method that considered travelers' bounded rationality to analyze selection results [26]. Zhang *et al.* proposed a multi-stage multi-attribute method based on online reviews for hotel evaluation in the longtime dimension [27]. (3) Studies on hotel customer satisfaction evaluation method based on online reviews. For instance, to discover a product or service's improvement priorities and allocate limited resources reasonably, Wu *et al.* proposed a novel method based on dynamic importance-performance analysis [28]. Ahani *et al.* took hotels in the Canary Islands as an example and used self-organizing map (SOM) and TOPSIS to determine travelers' preferences and satisfaction [29]. Using technologies such as LDA, Bi *et al.* extracted important product or service attributes that customers cared about and performed the IPA based on online reviews [30]. Sánchez-Franco *et al.* adopted a maximum relevance minimum redundancy (MRMR) method based on mutual information statistical measure to extract attributes from online reviews, and developed a naive Bayes classifier for sentiment classification [31]. For SPA hotels, Ahani *et al.* used SOM, HOSVD and CRT to develop a novel method for market segmentation and travel choice [32]. Hu *et al.* first identified attributes in online reviews, and after the performance and importance weights of attributes were obtained, they assessed the relationship between attributes and customer satisfaction using sentiment analysis and statistics methods. Finally, the results were visualized in 3D [33].

The existing studies have made significant contributions to the evaluation of hotel customer satisfaction based on online reviews. However, there are still some limitations in the existing studies. First, most of these studies do not consider the reliability of online reviews. That will reduce the evaluation results accuracy. In reality, online reviews on travel review websites come from different reviewers, and the reliability of the reviews varies due to the different knowledge, experience and preference of reviewers. For example, Leung and Yang pointed out that when two customers were equally satisfied with the hotel experience, a customer with a higher level might give lower ratings [34]. This difference in reliability leads to uncertainty of the evaluation information given by customers, which cannot be handled well by traditional MCDM methods [35]. The evidence theory proposed by Dempster and Shafer [36] is a useful method for dealing with uncertain evaluation information and providing a simple way to merge evaluation information from multiple sources. Second, most of these studies focus on a single website. In fact, online reviews of the same hotel often exist on multiple travel review websites. The simultaneous consideration of multiple websites can increase the amount of research data to improve the accuracy of evaluation and reveal the hotel's customer satisfaction more comprehensively by carefully considering the attributes set by different websites. However, the differences in preset attributes and evaluation grades among websites make existing methods for a single website difficult to apply to multiple websites. In addition, most of the existing studies are based on textual reviews. When posting textual reviews, customers will only evaluate the attributes they care about, which makes the structured data transformed from textual reviews relatively sparse [37]. That makes it difficult to evaluate customer satisfaction with online textual reviews. In fact, the online review websites preset several attributes, allowing customers only to appraise these attributes, that is, the online ratings. Geetha *et al.* pointed out that textual reviews and online ratings are emotionally consistent [38]. Thus online ratings can be used for the research of hotel customer satisfaction. Therefore, to reveal the hotel customer satisfaction, a new customer satisfaction measurement method based on online ratings is necessary, which is this paper's motivation.

This paper aims to propose a method for measuring hotel customer satisfaction based on D-S evidence theory. In the proposed method, online evaluation information is first collected from multiple online travel review websites and processed to obtain the basic probability assignment considering its reliability. Then, the D-S evidence theory is used for the fusion of evaluation information. Finally, the utility function is used to calculate the utility value of customer satisfaction on each attribute and the expected utility value of overall customer satisfaction; in this way, customer satisfaction for the same type of hotel on different dimensions and overall level can be compared. The research results are expected to make meaningful contributions to the research on customer satisfaction and help hotel practitioners and researchers make a more realistic assessment of the impact of electronic word of mouth.

The remainder of the paper is organized in the following way. Section 2 briefly describes the problem of measuring hotel customer satisfaction considering the reliability of online reviews. Section 3 introduces a method for measuring customer satisfaction with the reliability of online reviews in mind. In Section 4, a case study of customer satisfaction for four hotels of the same type illustrates the proposed method's use. Finally, conclusions and future research direction are given in Section 5.

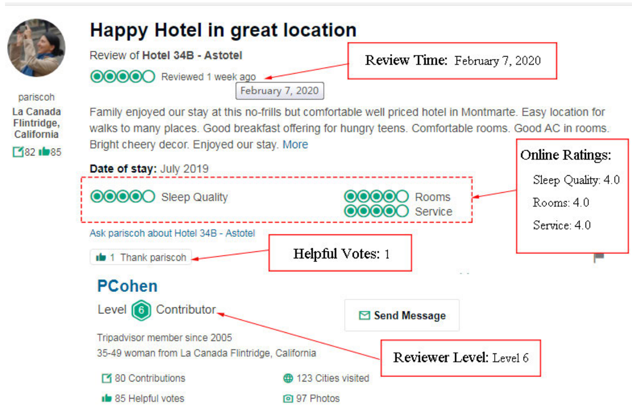

FIGURE 1. Screenshot of one online review sample on TripAdvisor. com.

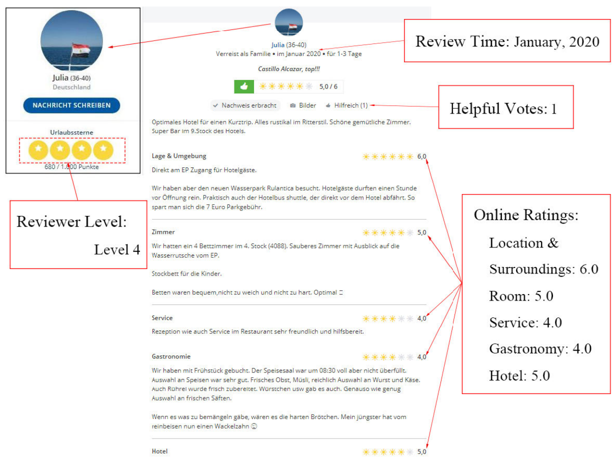

FIGURE 2. Screenshot of one online review sample on holidaycheck.de.

II. PROBLEM DESCRIPTION

After staying in a hotel, customers will post online reviews on online travel review websites, reflecting their satisfaction with the hotel to a certain extent. The online review interfaces of TripAdvisor and HolidayCheck are given respectively in Fig. 1 and Fig. 2. Generally, the website information includes reviewer level, online ratings, review time, helpful votes, among other items. The following information can be obtained from Fig. 1 and Fig. 2. First, online reviews differ in three aspects: review time, reviewer level, and helpful votes. As the hotel may improve service and facilities in the course of operation, reviews posted more recently reflect the hotel's current satisfaction. In addition, since the reviewer level reflects reviewer's evaluation experience, the review made by the reviewer with higher level is more objective and reliable. Furthermore, each review has helpful votes, representing the extent to which reviewers in the same online community approve the review. The more helpful votes a review obtains, the more reliable it is. Next, it should be noted that preset attributes differ among online review websites, which may be due to the differences in the various sites' core concerns. Therefore, consideration of multi-site evaluation information can evaluate hotel customer satisfaction more comprehensively. Secondly, the evaluation grade may differ among travel review websites. As shown, TripAdvisor adopts a 5-point scale as its evaluation grade (Fig. 1), whereas HolidayCheck uses a 6-point scale (Fig. 2). Therefore, in the measurement of customer satisfaction, the difference in evaluation grades needs to be handled.

As mentioned above, such information is essential for measuring customer satisfaction; thus this paper utilizes such information in revealing customer satisfaction of the hotel. Then, the problem to be solved in this paper is to measure hotel customer satisfaction with such information and determine the order of improving hotel customer satisfaction for each attribute.

The following notations are used to denote the sets and variables in the problem:

- $W = \{W^1, W^2, \ldots, W^L\}$: the set of L online travel review websites, where W^l denotes the lth online travel review website, $l = 1, 2, \ldots, L$.
- $A = \{a_1, a_2, \ldots, a_N\}$: the set of N hotels of the same type, where a_n denotes the nth hotel, $n = 1, 2, \ldots, N$.
- $E = \{e_1, e_2, \ldots, e_J\}$: the set of J hotel attributes, where e_j denotes the jth hotel attribute, $j = \{1, 2, \ldots, J\}$.
- $\omega = \{\omega_1, \omega_2, \ldots, \omega_J\}$: the set of attribute weights, where ω_j denotes the weight of attribute e_j, such that $\omega_j \geq 0$ and $\sum_{j=1}^{J} \omega_j = 1, j = \{1, 2, \ldots, J\}$.
- $\Theta = \{H_1, H_2, \ldots, H_I\}$: the set of I evaluation grades, where H_i denotes the ith evaluation grade, $i = 1, 2, \ldots, I$.Without the loss of generality, it is assumed that H_{i+1} is preferred to H_i, $i = 1, 2, \ldots, I-1$. For example, when $I = 5$, i.e. $\Theta = \{H_1, H_2, \ldots, H_5\}$, H_1 and H_5 are set to the worst and the best grades, respectively.
- $\Theta^l = \{H_1^l, H_2^l, \ldots, H_{I_l}^l\}$: the set of I_l evaluation grades on website W^l, where H_t^l denotes the tth evaluation grade on website W^l, $t = 1, 2, \ldots, I_l$, $l = 1, 2, \ldots, L$.
- u_i : the utility of evaluation grade H_i, $i = 1, 2, \ldots, I$.
- u_t^l : the utility of evaluation grade H_t^l, $t = 1, 2, \ldots, I_l$, $l = 1, 2, \ldots, L$.
- P_n^l : the total number of online reviews about hotel a_n on website W^l, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- G^l : the maximum of reviewer level on website W^l, $l = 1, 2, \ldots, L$.
- $g_n^{l,p}$: the reviewer level corresponding to the p th review about hotel a_n on website W^l, $p = 1, 2, \ldots, P_n^l$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- $d_n^{l,p}$: the duration between the review time of the pth review about hotel a_n on website W^l and the measure time of customer satisfaction, in the unit of the day, $p = 1, 2, \ldots, P_n^l$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- $d_n^{l,*}$: the duration between the earliest review time of all reviews about hotel a_n on website W^l and the measure time of customer satisfaction, in the unit of the day, i.e., $d_n^{l,*} = \max_p(d_n^{l,p})$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.

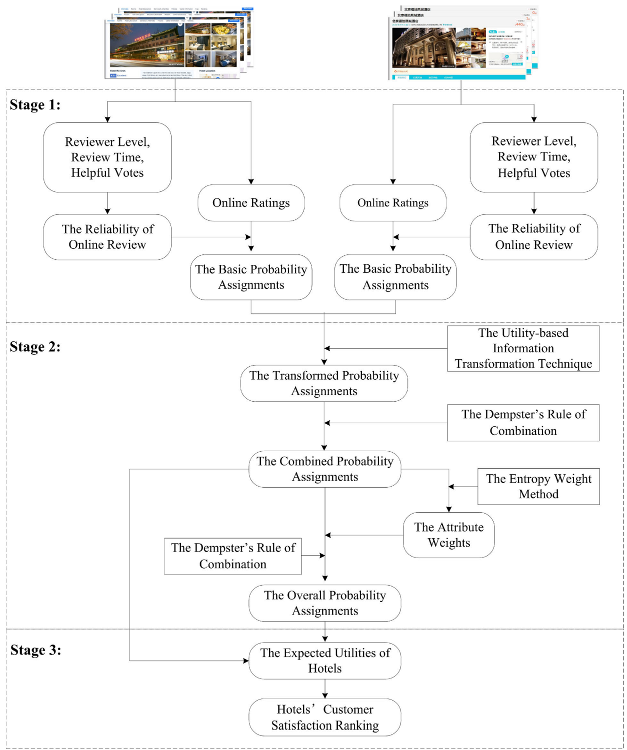

FIGURE 3. The resolution procedure for measuring hotel customer satisfaction.

- $v_n^{l,p}$: the number of helpful votes obtained by the pth review about hotel a_n on website W^l, $p = 1, 2, \ldots, P_n^l$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- $v_n^{l,*}$: the maximum number of helpful votes obtained by all reviews about hotel a_n on website W^l, i.e., $v_n^{l,*} = \max_p(v_n^{l,p})$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- $r_n^{l,p}$: the reliability of the pth review of hotel a_n on website W^l, $p = 1, 2, \ldots, P_n^l$, $n = 1, 2, \ldots, N$, $l = 1, 2, \ldots, L$.
- $u_{j,n}$: the expected utility of customer satisfaction with attribute e_j of hotel a_n, $j = \{1, 2, \ldots, J\}$, $n = 1, 2, \ldots, N$.
- u_n : the expected utility of customer satisfaction with hotel a_n, $n = 1, 2, \ldots, N$.

III. THE METHOD

To solve the above problem, we present a new method for measuring hotel customer satisfaction considering the reliability of online reviews in this section. The resolution procedure of the method is shown in Fig. 3. It can be seen from Fig. 3 that the method is composed of the following three stages:

- Stage 1: Generating the basic probability assignments from online reviews.
- Stage 2: Aggregating online reviews.
- Stage 3: Calculating the expected utility and ranking customer satisfaction.

In the first stage, online evaluation information of hotels is collected from multiple online travel review websites, including online ratings for each attribute, review time, reviewer level, and helpful votes; then, the reliability of each review is calculated with the reviewer level, review time, and helpful votes; further, based on the obtained reliability and online ratings, basic probability assignments are obtained from online reviews. In the second stage, the information from different websites is first transformed into a unified frame of discernment using the rule-based information transformation technique; the transformed information is then aggregated on each attribute with Dempster's rule of combination; finally, the weight of each attribute is calculated using the entropy weight method, and the information aggregation on each hotel is conducted based on Dempster's rule of combination. In the final stage, the combined probability assignments and the overall probability assignments are converted to the expected utility that is easy to compare; then, the ranking of customer satisfaction is conducted based on the obtained expected utility so that the hotel can make customer satisfaction improvement plans.

A. GENERATING THE BASIC PROBABILITY ASSIGNMENTS FROM ONLINE REVIEWS

1) EVIDENCE THEORY

Evidence theory was first proposed by American scholar Dempster in 1967 and further developed and refined by Shafer in his book *A Mathematical Theory of Evidence* [39]. Therefore, this theory is also called the Dempster-Shafer theory of evidence, or the D-S theory for short. Due to its ability to deal with uncertainty, the D-S evidence theory is applied to information fusion in the field of decision making [40], [41]. To facilitate understanding of the proposed method, this section will briefly introduce the basic definitions of evidence theory.

Definition 1: [39], [42] For one decision problem, the possible results that we know or think we know are expressed in the set Θ, and any propositions we interest are in a one-to-one correspondence with the subset of Θ. Set Θ is called the frame of discernment, a finite set of mutually exclusive and exhaustive propositions. For example, a website's attributes can be evaluated on four grades, thus, the frame of discernment for the website is $\Theta = \{H_1, H_2, H_3, H_4\}$.

Definition 2: [36], [43] Let Θ be a frame of discernment. A basic probability assignment is a mapping $m : 2^{\Theta} \to [0, 1]$, which is called a mass function and satisfies:

$$m(\phi) = 0 \text{ and } \sum_{A\subseteq\Theta} m(A) = 1$$

where 2^{Θ} is the power set of Θ, ϕ is the empty set, and A is any subset of Θ. The quantity $m(A)$ is called the basic probability number of proposition A, which measures the belief exactly assigned to A and represents how strongly the evidence supports A.

Definition 3: [36], [44] Dempster's rule of combination is the kernel of D-S theory by which evidence from different sources is combined or aggregated. Let m_1 and m_2 be two basic probability assignments that are derived from two distinct sources. For propositions $A, B \subseteq \Theta$, Dempster's rule is given as follows:

$$m(C) = m_1(A) \oplus m_2(B) = \begin{cases} 0, & C = \phi \\ \dfrac{\sum_{A\cap B=C} m_1(A)m_2(B)}{1 - \sum_{A\cap B=\phi} m_1(A)m_2(B)}, & C \neq \phi \end{cases}$$

where $\oplus$ represents the operator of the combination, the denominator $1 - \sum_{A\cap B=\phi} m_1(A)m_2(B)$ is called the normalization factor and $\sum_{A\cap B=\phi} m_1(A)m_2(B)$ is called the degree of conflict that measures the conflict between the pieces of evidence.

2) CALCULATING THE RELIABILITY OF ONLINE REVIEWS

There are differences in the reviewer's experience, review time and helpful votes; thus, online review reliability is diverse. Above all, customers' online reviews will be affected by their own previous experiences with accommodation and evaluation. For one customer, the more experience the person has with accommodation and evaluation, the more reliable the review. In addition, the release time and the helpful votes of online review will also influence its reliability. The closer the release time of a review is, the more it can reflect the hotel's current customer satisfaction, and the higher the reliability of the review is. Similarly, the helpful votes show how many customers agree with the review. The more helpful votes a review obtains, the more reliable it is for expressing customer satisfaction. Therefore, this paper uses the reviewer level, review time, and helpful votes of online reviews as the influencing factors for reliability and combines the three to calculate an online review's reliability.

First, due to the different dimensions of reviewer level, review time and helpful votes, a dimensionless treatment of the three items is adopted. The calculation process is as follows:

- The reviewer level

$$X_{1,n}^{l,p} = \frac{g_n^{l,p}}{G^l} \tag{1}$$

- The review time

$$X_{2,n}^{l,p} = \exp\left(-\frac{d_n^{l,p}}{d_n^{l,*}}\right) \tag{2}$$

- The helpful votes

$$X_{3,n}^{l,p} = \begin{cases} \dfrac{v_n^{l,p}}{v_n^{l,*}}, & v_n^{l,*} \neq 0 \\ 0, & v_n^{l,*} = 0 \end{cases} \tag{3}$$

Then, according to the data after normalization, the reliability of evaluation information is calculated. Suppose reviewer level, review time, and helpful votes are of equal importance, the reliability $r_n^{l,p}$ is as follows:

$$r_n^{l,p} = (X_{1,n}^{l,p} + X_{2,n}^{l,p} + X_{3,n}^{l,p})/3 \tag{4}$$

3) OBTAINING THE BASIC PROBABILITY ASSIGNMENTS

Before evidence combination by D-S theory of evidence, the basic probability assignments required in the combination rule need to be generated from online reviews. When a customer releases an online review concerning the hotel experience, the customer will give each attribute set by the website a rating. Suppose in the pth review of hotel a_n on website W^l, a customer evaluates attribute e_j as grade H_y^l; thus, the review given by the customer for attribute e_j can be expressed as follows:

$$\lambda_{t,j,n}^{l,p} = \begin{cases} 0, & t \neq y \\ 1, & t = y, \end{cases} \quad t = 1, 2, \ldots, I_l \tag{5}$$

For example, in the pth review of hotel a_n on website W^l, a customer evaluates attribute e_j as grade H_3^l, thus the review given by the customer for attribute e_j can be expressed as $\lambda_{3,j,n}^{l,p} = 1; \lambda_{t,j,n}^{l,p} = 0, t \neq 3$.

Therefore, the basic probability assignment $\beta_{t,j,n}^l$, which represents the probability assignment to which attribute e_j of hotel a_n is assessed to grade H_t^l on website W^l, $t = 1, 2, \ldots, I_l$, $l = 1, 2, \ldots, L$, $j = 1, 2, \ldots, J$, $n = 1, 2, \ldots, N$, can be calculated by

$$\beta_{t,j,n}^l = \begin{cases} 0, & H_t^l = \phi \\ \dfrac{\sum_{p=1}^{P_n^l} r_n^{l,p} \lambda_{t,j,n}^{l,p}}{\sum_{p=1}^{P_n^l} r_n^{l,p}}, & H_t^l \neq \phi, H_t^l \in \Theta^l \end{cases} \tag{6}$$

B. AGGREGATING ONLINE REVIEWS

1) TRANSFORMING MULTI-SITE INFORMATION INTO THE UNIFIED FRAME OF DISCERNMENT

The evaluation grades set by different online travel review websites may be diverse. For example, Booking sets its evaluation grade as 10-point scale, whereas TripAdvisor and HolidayCheck adopt 5-point and 6-point scales, respectively. To clarify how online reviews on different websites reflect the overall satisfaction of the hotel, it is necessary to transform various sets of evaluation grades to a unified set before multi-site evaluation information fusion, so as to evaluate all attributes in a consistent and compatible manner. According to Yang, there are two ways to transform: the rule-based technique and the utility-based technique [45]. The utility-based information transformation technique is employed in this paper.

First, the utilities for the unified evaluation grade and evaluation grades on different websites are calculated, respectively. Suppose the utility follows the equidistant distribution of the interval [0,1]. The specific calculation process is as follows:

$$u_t^l = \frac{t-1}{I_l - 1}, \quad t = 1, 2, \ldots, I_l; l = 1, 2, \ldots, L \tag{7}$$

$$u_i = \frac{i-1}{I-1}, \quad i = 1, 2, \ldots, I \tag{8}$$

Next, the information from multiple websites is transformed into a unified frame of discernment. The transformed basic probability assignment function $m_{i,j,n}^l$ is given by the following equations:

$$m_{i,j,n}^l = \begin{cases} \sum_{t\in\pi_i} \beta_{t,j,n}^l \tau_{i,t}, & i = 1 \\ \sum_{t\in\pi_{i-1}} \beta_{t,j,n}^l (1-\tau_{i-1,t}) + \sum_{t\in\pi_i} \beta_{t,j,n}^l \tau_{i,t}, & 2 \leq i \leq I-1 \\ \sum_{t\in\pi_{i-1}} \beta_{t,j,n}^l (1-\tau_{i-1,t}), & i = I \end{cases} \tag{9}$$

where

$$\pi_i = \begin{cases} \{t | u_i \leq u_t^l < u_{i+1}, t = 1, 2, \ldots, I_l\}, & i = 1, \ldots I-2 \\ \{t | u_i \leq u_t^l \leq u_{i+1}, t = 1, 2, \ldots, I_l\}, & i = I-1 \end{cases} \tag{10}$$

and

$$\tau_{i,t} = \frac{u_{i+1} - u_t^l}{u_{i+1} - u_i}, \quad \text{if } u_i \leq u_t^l \leq u_{i+1} \tag{11}$$

To facilitate understanding, an example is given now. There is the basic probability assignment $\beta_{t,j,n}^l$, where $t = 1, 2, 3$, and the frame of discernment for website W^l is $\Theta^l = \{H_1^l, H_2^l, H_3^l\}$. The calculation process of transforming the basic probability assignments to the unified frame of discernment $\Theta = \{H_1, H_2, \ldots, H_5\}$ is as follows:

From Equation (7), the utilities of the frame of discernment Θ^l are

$$u_1^l = 0, u_2^l = 0.5, u_3^l = 1$$

From Equation (8), the utilities of the unified frame of discernment Θ are

$$u_1 = 0, u_2 = 0.25, u_3 = 0.50, u_4 = 0.75, u_5 = 1$$

From Equation (10), we have

$$\pi_1 = \{1\}, \pi_2 = \phi, \pi_3 = \{2\}, \ \pi_4 = \{3\}$$

From Equation (9), we have

$$m_{1,j,n}^l = \sum_{t\in\pi_1} \beta_{t,j,n}^l \tau_{1,t} = \beta_{1,j,n}^l \tau_{1,1}$$

$$\begin{aligned} m_{2,j,n}^l &= \sum_{t\in\pi_1} \beta_{t,j,n}^l (1-\tau_{1,t}) + \sum_{t\in\pi_2} \beta_{t,j,n}^l \tau_{2,t} \\ &= \beta_{1,j,n}^l (1-\tau_{1,1}) \end{aligned}$$

$$m_{3,j,n}^l = \sum_{t\in\pi_2} \beta_{t,j,n}^l (1-\tau_{2,t}) + \sum_{t\in\pi_3} \beta_{t,j,n}^l \tau_{3,t} = \beta_{2,j,n}^l \tau_{3,2}$$

$$\begin{aligned} m_{4,j,n}^l &= \sum_{t\in\pi_3} \beta_{t,j,n}^l (1-\tau_{3,t}) + \sum_{t\in\pi_4} \beta_{t,j,n}^l \tau_{4,t} \\ &= \beta_{2,j,n}^l (1-\tau_{3,2}) + \beta_{3,j,n}^l \tau_{4,3} \end{aligned}$$

$$m_{5,j,n}^l = \sum_{t\in\pi_4} \beta_{t,j,n}^l (1-\tau_{4,t}) = \beta_{3,j,n}^l (1-\tau_{4,3})$$

From Equation (11), we have

$$\tau_{1,1} = 1, \tau_{3,2} = 1, \tau_{4,3} = 0$$

Therefore, the results of the information transformation for website W^l are as follows:

$$m^l_{1,j,n} = \beta^l_{1,j,n}, m^l_{3,j,n} = \beta^l_{2,j,n}, m^l_{5,j,n} = \beta^l_{3,j,n}$$

2) AGGREGATING THE INFORMATION FROM DIFFERENT WEBSITES ON EACH ATTRIBUTE

The combined probability assignment $m_{i,j,n}$, which represents the probability assignment to which attribute e_j of hotel a_n is assessed to grade H_i, can be generated by aggregating the evaluation information of attribute e_j of hotel a_n on all the L websites. The specific aggregation process is as follows (12), as shown at the bottom of the page, where

$$K = \left[1 - \sum_{\substack{H_{i_1},\ldots,H_{i_L} \in \Theta \\ H_{i_1} \cap \cdots \cap H_{i_L} = \phi}} m^1_{i_1,j,n} \cdots m^L_{i_L,j,n} \right]^{-1} \tag{13}$$

3) CALCULATING THE WEIGHTS OF ATTRIBUTES

The measurement of hotel customer satisfaction is based on customers' online reviews; thus, it is necessary to determine the attribute weight objectively. However, the subjective weighting method determines weights based on the degree to which the decision-maker attaches subjective importance to each attribute and reflects their subjective intention. The subjective intention of the decision-maker may interfere with evaluation results, making it unable to truly reveal customer satisfaction for a hotel. In addition, when determining the attribute weight, the change of the attribute value needs to be taken into account. If the value of a certain attribute changes greatly among different customers, there is a big difference in customer opinions against this attribute. Therefore, this attribute needs to be paid more attention to when evaluating customer satisfaction. In contrast, if a certain attribute's value does not vary much, customer opinions tend to be consistent. The attention to the attribute can be appropriately reduced when evaluating customer satisfaction. Given this, this paper applies the entropy weight method to determine the attribute weight.

The entropy weight method is a widely used method to determine attribute weights based on attribute differences. This method's principle is that the greater the difference of attribute values, the smaller the information entropy, the more information provided by attribute values, and the greater the weight of the attribute, and vice versa. The calculation result is more objective, and the decision result is more reliable. The specific calculation process is as follows [46] :

Step 1: Standardized processing.

$$f_{j,n} = \sum_{i=1}^{I} m_{i,j,n} \bullet u_i, \quad j = 1, 2, \ldots J; n = 1, 2, \ldots N \tag{14}$$

Step 2: Calculating information entropy.

$$E_j = -\frac{\sum_{n=1}^{N} p_{j,n} \ln p_{j,n}}{\ln (N)}, \quad j = 1, 2, \ldots, J \tag{15}$$

where

$$p_{j,n} = \frac{f_{j,n}}{\sum_{n=1}^{N} f_{j,n}}, \quad j = 1, 2, \ldots J \tag{16}$$

Step 3: Determining the attribute weight

$$\omega_j = \frac{1 - E_j}{\sum_{j=1}^{J} \left(1 - E_j\right)}, \quad j = 1, 2, \ldots, J \tag{17}$$

4) AGGREGATING THE INFORMATION OF MULTIPLE ATTRIBUTES ON EACH HOTEL

Let the evaluation grades set $\Theta = \{H_1, H_2, \ldots, H_I\}$ be regarded as the unified frame of discernment. The combined probability assignment $m_{i,j,n}$ is further aggregated to generate the overall probability assignment for hotels.

First, suppose $m'_{i,j,n}$ is the intermediate probability assignment to which attribute e_j of hotel a_n is confirmed to grade H_i considering the attribute weight ω_j. The combined probability assignment $m_{i,j,n}$ needs to be converted to the intermediate probability assignment $m'_{i,j,n}$ by combining with attribute weights using the following equation:

$$m'_{i,j,n} = \begin{cases} 0, & H_i = \phi \\ \omega_j m_{i,j,n}, & H_i \neq \phi, H_i \in \Theta \\ 1 - \sum_{i=1}^{I} m'_{i,j,n}, & H_i = \Theta \end{cases} \tag{18}$$

Second, the evaluation information of hotel a_n on all the J attributes is aggregated into the overall evaluation, that is, the intermediate probability assignment $m'_{i,j,n}$ is aggregated to generate the overall probability assignment. Suppose $m_{i,n}$ expresses the overall probability assignment for evaluation of hotel a_n, $i = 1, 2, \ldots, I,\ n = 1, 2, \ldots, N$. The combination

$$m_{i,j,n} = \begin{cases} 0, & H_i = \phi \\ K \sum_{\substack{H_{i_1},\ldots,H_{i_L} \in \Theta \\ H_{i_1} \cap \cdots \cap H_{i_L} = H_i}} m^1_{i_1,j,n} m^2_{i_2,j,n} \cdots m^L_{i_L,j,n}, & H_i \neq \phi, H_i \in \Theta \end{cases} \tag{12}$$

process is as follows:

$$m_{i,n} = \begin{cases} 0, & H_i = \phi \\ K \bullet \sum\limits_{\substack{H_{i_1},\ldots,H_{i_J} \in \Theta \\ H_{i_1} \cap \cdots \cap H_{i_J} = H_i}} m'_{i_1,1,n} \cdots m'_{i_J,J,n}, & H_i \neq \phi, H_i \in \Theta \end{cases} \tag{19}$$

where

$$K = \left[1 - \sum_{\substack{H_{i_1},\ldots,H_{i_J} \in \Theta \\ H_{i_1} \cap \cdots \cap H_{i_J} = \phi}} m'_{i_1,1,n} \cdots m'_{i_J,J,n} \right]^{-1} \tag{20}$$

C. CALCULATING THE EXPECTED UTILITY AND RANKING CUSTOMER SATISFACTION

Through the above calculation, the combined probability assignments and the overall probability assignments can be obtained. For instance, for attribute e_1 of hotel a_1, the combined probability assignments are $m_{1,1,1} = 0.2$, $m_{2,1,1} = 0.3$, $m_{3,1,1} = 0.5$. The probability assignments are not conducive to comparing customer satisfaction with different attributes or different hotels. Thus, this paper employs the expected utility to compare and rank them. The expected utility of customer satisfaction with each attribute of hotel is calculated by

$$u_{j,n} = \sum_{i=1}^{I} \frac{m_{i,j,n}}{1 - m_{H,j,n}} u_i, \quad j = 1, 2, \ldots, J; n = 1, 2, \ldots, N \tag{21}$$

where $m_{H,j,n}$ denotes the probability assignment not to any grade.

Similarly, the expected utility of the overall customer satisfaction with each hotel is calculated by

$$u_n = \sum_{i=1}^{I} \frac{m_{i,n}}{1 - m_{H,n}} u_i, \quad n = 1, 2, \ldots, N \tag{22}$$

where $m_{H,n}$ denotes the probability assignment not to any grade.

Finally, the revelation of hotel customer satisfaction can be carried out by comparing expected utilities obtained from Equations (21) and (22).

If

$$u_{f,n} > u_{k,n}, \quad f \neq k; f, k = 1, 2, \ldots, J,$$

customer satisfaction with attribute e_f is better than attribute e_k for hotel a_n. Thus, the improvement of customer satisfaction of hotel a_n can start with attribute e_k.

Similarly, if

$$u_q > u_n, \quad q \neq n; q, n = 1, 2, \ldots, N,$$

the overall customer satisfaction of hotel a_q is superior to that of hotel a_n.

To sum up, the specific steps of the method to measure hotel customer satisfaction with online review reliability are provided below.

Step 1: Compute the reliability $r_n^{l,p}$ of online reviews using Equations (1) - (4).

Step 2: Convert online evaluation information into the basic probability assignment using Equations (5) and (6).

Step 3: Transform the information from multiple websites into the unified frame of discernment using Equations (7) - (11).

Step 4: Aggregate the transformed information on each attribute using Equations (12) and (13).

Step 5: Compute the attribute weight ω_j using Equations (14) - (17).

Step 6: Aggregate the information of multiple attributes on each hotel using Equations (18) - (20).

Step 7: Compute each attribute and hotel's expected utility using Equations (21) and (22) and rank customer satisfaction by comparing the computed expected utility.

IV. CASE STUDY

In this section, we describe a case study conducted to illustrate the effectiveness of the proposed method. First, the proposed method is used to evaluate the customer satisfaction of four mid-range business hotels. Next, comparisons between the proposed method and the existing method are presented.

A. EVALUATING CUSTOMER SATISFACTION WITH HOTELS

Four mid-range business hotels, i.e., FD, DJ, KM, and HI, are located in Beijing's Wangfujing business district. The related data of four hotels was collected from China's two major online travel review websites, i.e., Qunar (https://www.qunar.com) and Ctrip (https://www.ctrip.com). There are many online reviews for the hotels on the two websites. These online reviews reflect the real evaluations of the hotel's accommodation experience by customers and can be used to evaluate hotel's customer satisfaction.

First, the crawler tool GooSeeker (http://www.gooseeker.com) is applied to collect the related online reviews concerning FD (a_1), DJ (a_2), KM (a_3), and HI (a_4) from Qunar (W^1) and Ctrip (W^2). The five hotel attributes, i.e., service (e_1), facility (e_2), cleanliness (e_3), location (e_4), and environment (e_5), are selected as attributes for evaluating customer satisfaction by analyzing the collected online evaluations. Since both online ratings are quantified on a 5-point scale, from 1 (very dissatisfied) to 5 (very satisfied), the frames of discernment on Qunar (W^1) and Ctrip (W^2) are set to $\Theta^1 = \{H_1^1, H_2^1, \ldots, H_5^1\}$ and $\Theta^2 = \{H_1^2, H_2^2, \ldots, H_5^2\}$ respectively. Moreover, $\Theta = \{H_1, H_2, \ldots, H_5\}$ is set as the unified frame of discernment.

The reviewer level, review time, and helpful votes are normalized using Equations (1)-(3). Moreover, online review reliability can be calculated based on the normalized results using Equation (4). For instance, the online review in Fig. 4 is the first review for FD (a_1) on Ctrip (W^2) released on March 29, 2019, where the reviewer level is LEVEL 1,

FIGURE 4. An example of the collected data on Ctrip.com.

TABLE 1. The basic probability assignments of hotels on Qunar.

a_n	e_1	e_2	e_3	e_4
a_1	$\{(H_1^1,0.1121), (H_2^1,0.0307), (H_3^1,0.1095), (H_4^1,0.2319), (H_5^1,0.5159)\}$	$\{(H_1^1,0.0852), (H_2^1,0.0467), (H_3^1,0.1067), (H_4^1,0.2371), (H_5^1,0.5243)\}$	$\{(H_1^1,0.0271), (H_2^1,0.0523), (H_3^1,0.0558), (H_4^1,0.2611), (H_5^1,0.6037)\}$	$\{(H_1^1,0.0845), (H_2^1,0.0163), (H_3^1,0.1409), (H_4^1,0.2225), (H_5^1,0.5358)\}$
a_2	$\{(H_1^1,0.0305), (H_2^1,0), (H_3^1,0.0309), (H_4^1,0.1789), (H_5^1,0.7596)\}$	$\{(H_1^1,0.0305), (H_2^1,0.0307), (H_3^1,0.0383), (H_4^1,0.2567), (H_5^1,0.6438)\}$	$\{(H_1^1,0.0246), (H_2^1,0.0182), (H_3^1,0.0379), (H_4^1,0.2425), (H_5^1,0.6768)\}$	$\{(H_1^1,0.0187), (H_2^1,0), (H_3^1,0.0245), (H_4^1,0.1416), (H_5^1,0.8152)\}$
a_3	$\{(H_1^1,0.0629), (H_2^1,0.0364), (H_3^1,0.0820), (H_4^1,0.2015), (H_5^1,0.6172)\}$	$\{(H_1^1,0.0681), (H_2^1,0.0411), (H_3^1,0.1150), (H_4^1,0.2400), (H_5^1,0.5358)\}$	$\{(H_1^1,0.0498), (H_2^1,0.0424), (H_3^1,0.0985), (H_4^1,0.2279), (H_5^1,0.5814)\}$	$\{(H_1^1,0.0337), (H_2^1,0.0185), (H_3^1,0.0521), (H_4^1,0.1694), (H_5^1,0.7263)\}$
a_4	$\{(H_1^1,0.0202), (H_2^1,0), (H_3^1,0), (H_4^1,0.0671), (H_5^1,0.9127)\}$	$\{(H_1^1,0.0202), (H_2^1,0), (H_3^1,0.0228), (H_4^1,0.0954), (H_5^1,0.8616)\}$	$\{(H_1^1,0.0202), (H_2^1,0), (H_3^1,0.0141), (H_4^1,0.0589), (H_5^1,0.9068)\}$	$\{(H_1^1,0.0202), (H_2^1,0), (H_3^1,0), (H_4^1,0.0364), (H_5^1,0.9434)\}$

helpful votes are 1, and the online ratings for service, facility, cleanliness, and environment are 2, 4, 4, and 3 respectively. By analyzing all online reviews of FD (a_1) on Ctrip (W^2), we find the highest level of reviewer is LEVEL 3, and the maximum number of helpful votes is 11, that is $G^2 = 3$, $v_1^{2,*} = 11$. In addition, the earliest review time is August 14, 2016, and the time of measuring customer satisfaction is August 23, 2019, that is $d_1^{2,*} = 1104$, $d_1^{2,1} = 147$. Therefore, the results after normalization are $X_{1,1}^{2,1} = 0.3333$, $X_{2,1}^{2,1} = 0.8753$ and $X_{3,1}^{2,1} = 0.0909$, and the reliability of the review is $r_1^{2,1} = 0.4332$.

Next, the online review's conversion to the basic probability assignment $\beta_{t,j,n}^{l}$, $l = 1, 2$, $t = 1, 2, 3, 4, 5$, $j = 1, 2, 3, 4, 5$, $n = 1, 2, 3, 4$ is conducted using Equations (5) and (6). The results for the two websites are provided in TABLE 1 and TABLE 2, respectively.

The basic probability assignments from the two websites are aggregated on each attribute to generate the combined

TABLE 2. The basic probability assignments of hotels on Ctrip.

a_n	e_1	e_2	e_3	e_5
a_1	$\{(H_1^2,0.0511), (H_2^2,0.0319), (H_3^2,0.0867), (H_4^2,0.1997), (H_5^2,0.6306)\}$	$\{(H_1^2,0.0423), (H_2^2,0.0272), (H_3^2,0.1000), (H_4^2,0.2299), (H_5^2,0.6005)\}$	$\{(H_1^2,0.0318), (H_2^2,0.0187), (H_3^2,0.0645), (H_4^2,0.2010), (H_5^2,0.6840)\}$	$\{(H_1^2,0.0353), (H_2^2,0.0344), (H_3^2,0.0919), (H_4^2,0.2154), (H_5^2,0.6230)\}$
a_2	$\{(H_1^2,0.0221), (H_2^2,0.0042), (H_3^2,0.0548), (H_4^2,0.1806), (H_5^2,0.7384)\}$	$\{(H_1^2,0.0253), (H_2^2,0.0152), (H_3^2,0.1117), (H_4^2,0.2534), (H_5^2,0.5943)\}$	$\{(H_1^2,0.0181), (H_2^2,0.0159), (H_3^2,0.0628), (H_4^2,0.1858), (H_5^2,0.7174)\}$	$\{(H_1^2,0.0151), (H_2^2,0.0094), (H_3^2,0.0779), (H_4^2,0.1890), (H_5^2,0.7086)\}$
a_3	$\{(H_1^2,0.0534), (H_2^2,0.0266), (H_3^2,0.0724), (H_4^2,0.2300), (H_5^2,0.6176)\}$	$\{(H_1^2,0.0588), (H_2^2,0.0291), (H_3^2,0.1115), (H_4^2,0.2552), (H_5^2,0.5453)\}$	$\{(H_1^2,0.0382), (H_2^2,0.0226), (H_3^2,0.0707), (H_4^2,0.2182), (H_5^2,0.6502)\}$	$\{(H_1^2,0.0311), (H_2^2,0.0132), (H_3^2,0.0510), (H_4^2,0.2055), (H_5^2,0.6992)\}$
a_4	$\{(H_1^2,0.0125), (H_2^2,0.0066), (H_3^2,0.0247), (H_4^2,0.0739), (H_5^2,0.8823)\}$	$\{(H_1^2,0.0137), (H_2^2,0.0067), (H_3^2,0.0312), (H_4^2,0.1116), (H_5^2,0.8367)\}$	$\{(H_1^2,0.0104), (H_2^2,0.0050), (H_3^2,0.0197), (H_4^2,0.0789), (H_5^2,0.8859)\}$	$\{(H_1^2,0.0093), (H_2^2,0.0051), (H_3^2,0.0245), (H_4^2,0.0966), (H_5^2,0.8645)\}$

probability assignments $m_{i,j,n}$, $i = 1, 2, 3, 4, 5, j = 1, 2, 3, 4, 5$, $n = 1, 2, 3, 4$ by Equations (12) and (13). The results are shown in TABLE 3.

According to Equations (14)-(17), the computed attribute weights are $\omega_1 = 0.0512$, $\omega_2 = 0.0695$, $\omega_3 = 0.0239$, $\omega_4 = 0.6620$, $\omega_5 = 0.1934$, and then the combined probability assignments of the five attributes can be aggregated by Equations (18)-(20). The results are provided in TABLE 4.

With the aid of Equation (21), the expected utilities of different attributes are computed and then the results are plotted as Fig. 5. In Fig. 5, the utilities of the five attributes of hotel HI are relatively big; thus, hotel HI satisfies customers in various attributes. However, those of hotel FD are relatively small; thus, its customer satisfaction is relatively poor. The four hotels' customer satisfaction is close for the three attributes of service, facility, and cleanliness. However, for the other two attributes (i.e., environment and location), the satisfaction among hotels is quite diverse. Especially for the location attribute, the difference in the utility between hotel FD and hotel HI is the largest. At the same time, the utility of the location attribute is the smallest of all the utilities of hotel FD, which means that the location attribute belongs to the shortcomings of hotel FD. If hotel FD intends to improve customer satisfaction to enhance its competitiveness in the trading area, it can start with location.

The expected utility of each hotel can be calculated by Equation (22), and then the ranking of customer satisfaction of the four hotels is conducted. The result of ranking customer satisfaction is $HI \succ DJ \succ KM \succ FD$ in TABLE 4. Therefore, hotel HI has the best overall customer

TABLE 3. The combined probability assignments of hotels.

a_n	e_1	e_2	e_3	e_4	e_5
a_1	$\{(H_1,0.0148),(H_2,0.0025),(H_3,0.0245),(H_4,0.1194),(H_5,0.8388)\}$	$\{(H_1,0.0094),(H_2,0.0033),(H_3,0.0277),(H_4,0.1416),(H_5,0.8180)\}$	$\{(H_1,0.0018),(H_2,0.0021),(H_3,0.0076),(H_4,0.1115),(H_5,0.8770)\}$	$\{(H_1,0.0845),(H_2,0.0163),(H_3,0.1409),(H_4,0.2225),(H_5,0.5358)\}$	$\{(H_1,0.0353),(H_2,0.0344),(H_3,0.0919),(H_4,0.2154),(H_5,0.6230)\}$
a_2	$\{(H_1,0.0011),(H_2,0),(H_3,0.0028),(H_4,0.0542),(H_5,0.9418)\}$	$\{(H_1,0.0017),(H_2,0.0010),(H_3,0.0094),(H_4,0.1436),(H_5,0.8443)\}$	$\{(H_1,0.0008),(H_2,0.0005),(H_3,0.0045),(H_4,0.0844),(H_5,0.9097)\}$	$\{(H_1,0.0187),(H_2,0),(H_3,0.0245),(H_4,0.1416),(H_5,0.8152)\}$	$\{(H_1,0.0151),(H_2,0.0094),(H_3,0.0779),(H_4,0.1890),(H_5,0.7086)\}$
a_3	$\{(H_1,0.0077),(H_2,0.0022),(H_3,0.0136),(H_4,0.1058),(H_5,0.8707)\}$	$\{(H_1,0.0108),(H_2,0.0032),(H_3,0.0345),(H_4,0.1649),(H_5,0.7866)\}$	$\{(H_1,0.0043),(H_2,0.0022),(H_3,0.0159),(H_4,0.1137),(H_5,0.8639)\}$	$\{(H_1,0.0337),(H_2,0.0185),(H_3,0.0521),(H_4,0.1694),(H_5,0.7263)\}$	$\{(H_1,0.0311),(H_2,0.0132),(H_3,0.0510),(H_4,0.2055),(H_5,0.6992)\}$
a_4	$\{(H_1,0.0003),(H_2,0),(H_3,0),(H_4,0.0061),(H_5,0.9936)\}$	$\{(H_1,0.0004),(H_2,0),(H_3,0.0010),(H_4,0.0145),(H_5,0.9841)\}$	$\{(H_1,0.0003),(H_2,0),(H_3,0.0003),(H_4,0.0057),(H_5,0.9937)\}$	$\{(H_1,0.0202),(H_2,0),(H_3,0),(H_4,0.0364),(H_5,0.9434)\}$	$\{(H_1,0.0093),(H_2,0.0051),(H_3,0.0245),(H_4,0.0966),(H_5,0.8645)\}$

TABLE 4. The overall probability assignments and ranking of hotels.

a_n	$m_{i,n}$	u_n	ranking
a_1	$\{(H_1,0.0474),(H_2,0.0110),(H_3,0.0827),(H_4,0.1445),(H_5,0.4467),(H,0.2677)\}$	0.8182	4
a_2	$\{(H_1,0.0103),(H_2,0.0006),(H_3,0.0174),(H_4,0.0905),(H_5,0.6272),(H,0.2540)\}$	0.9436	2
a_3	$\{(H_1,0.0195),(H_2,0.0103),(H_3,0.0310),(H_4,0.1104),(H_5,0.5699),(H,0.2588)\}$	0.9050	3
a_4	$\{(H_1,0.0102),(H_2,0.0003),(H_3,0.0014),(H_4,0.0237),(H_5,0.7223),(H,0.2421)\}$	0.9775	1

satisfaction among the four hotels, whereas hotel FD has the worst.

B. COMPARING THE PROPOSED METHOD WITH THE EXISTING METHOD

A comparison with the method provided by Fan *et al.* [47] is conducted to investigate the advantages and characteristics of the proposed method. It is necessary to point out that, although the method of Fan *et al.* can be used to rank the customer satisfaction of the hotel based on online reviews, the attribute weights in their method are determined according to customers' subjective preferences instead of online reviews. Thus, we assume that the set of attribute weights provided by customers is $\omega = \{0.0512, 0.0695, 0.0239, 0.6620, 0.1934\}$. Next, the method provided by Fan *et al.* is used for evaluating the four mid-range business hotels.

First, denoise processing is conducted, and the processed evaluations are used to calculate the discrete percentage distributions. The results are shown in TABLE 5.

Second, according to the discrete percentage distributions and stochastic dominance rules, pairwise comparisons of the four hotels concerning each attribute are conducted to determine the stochastic dominance relation st_{nqj}, and set up the corresponding stochastic dominance relation matrix $ST_j = [st_{nqj}]_{4\times 4}$, $n, q = 1, 2, 3, 4$, $j = 1, 2, 3, 4, 5$. st_{nqj} = "–" denotes there is no stochastic dominance relation between two hotels a_n and a_q for attribute e_j, and FSD denotes first degree stochastic dominance.

$$ST_1 = \begin{bmatrix} - & - & - & - \\ FSD & - & FSD & - \\ FSD & - & - & - \\ FSD & FSD & FSD & - \end{bmatrix}$$

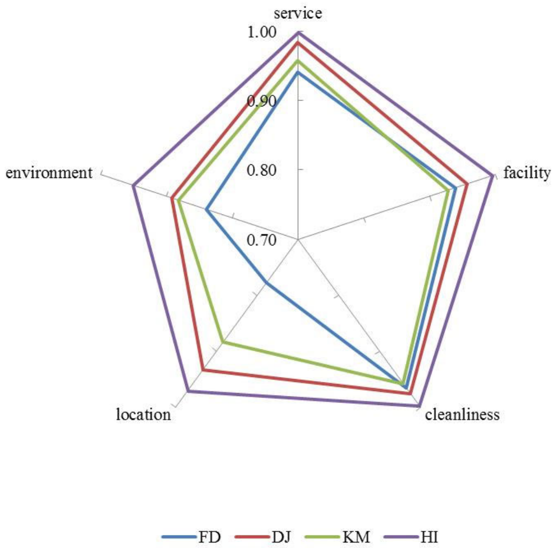

FIGURE 5. The expected utility of hotels on each attribute.

$$ST_2 = \begin{bmatrix} - & - & FSD & - \\ FSD & - & FSD & - \\ - & - & - & - \\ FSD & FSD & FSD & - \end{bmatrix}$$

$$ST_3 = \begin{bmatrix} - & - & FSD & - \\ FSD & - & FSD & - \\ - & - & - & - \\ FSD & FSD & FSD & - \end{bmatrix}$$

$$ST_4 = \begin{bmatrix} - & - & - & - \\ FSD & - & FSD & - \\ FSD & - & - & - \\ FSD & FSD & FSD & - \end{bmatrix}$$

$$ST_5 = \begin{bmatrix} - & - & - & - \\ FSD & - & FSD & - \\ FSD & - & - & - \\ FSD & FSD & FSD & - \end{bmatrix}$$

In addition, the stochastic dominance degree sd_{nqj} for pair-wise comparisons of the four hotels for each attribute can be calculated. Moreover, the stochastic dominance degree matrix $SD_j = [sd_{nqj}]_{4\times4}, n, q = 1, 2, 3, 4, j = 1, 2, 3, 4, 5$ can be set up as follows.

$$SD_1 = \begin{bmatrix} - & - & - & - \\ 0.2624 & - & 0.1318 & - \\ 0.1505 & - & - & - \\ 0.3811 & 0.1609 & 0.2715 & - \end{bmatrix},$$

$$SD_2 = \begin{bmatrix} - & - & 0.1341 & - \\ 0.0554 & - & 0.1820 & - \\ - & - & - & - \\ 0.2480 & 0.2039 & 0.3489 & - \end{bmatrix},$$

TABLE 5. The discrete percentage distributions for the four hotels concerning the five attributes.

a_n	Θ	e_1	e_2	e_3	e_4	e_5
a_1	H_1	0.0644	0.0000	0.0000	0.0881	0.0000
	H_2	0.0302	0.0312	0.0196	0.0167	0.0367
	H_3	0.0921	0.1084	0.0678	0.1357	0.0966
	H_4	0.2003	0.2402	0.2068	0.2143	0.2227
	H_5	0.6130	0.6201	0.7058	0.5452	0.6439
a_2	H_1	0.0000	0.0000	0.0000	0.0000	0.0000
	H_2	0.0000	0.0166	0.0000	0.0000	0.0000
	H_3	0.0556	0.0894	0.0623	0.0524	0.0528
	H_4	0.1666	0.2362	0.1800	0.1931	0.1563
	H_5	0.7778	0.6578	0.7578	0.7545	0.7909
a_3	H_1	0.0000	0.0567	0.0000	0.0000	0.0000
	H_2	0.0288	0.0304	0.0261	0.0665	0.0000
	H_3	0.0763	0.1112	0.0777	0.0526	0.0531
	H_4	0.2326	0.2504	0.2253	0.1607	0.2088
	H_5	0.6623	0.5513	0.6710	0.7202	0.7380
a_4	H_1	0.0000	0.0000	0.0000	0.0000	0.0000
	H_2	0.0000	0.0000	0.0000	0.0000	0.0000
	H_3	0.0000	0.0288	0.0000	0.0000	0.0000
	H_4	0.0722	0.1085	0.0765	0.0333	0.0955
	H_5	0.9278	0.8627	0.9235	0.9667	0.9045

$$SD_3 = \begin{bmatrix} - & - & 0.0394 & - \\ 0.0691 & - & 0.1434 & - \\ - & - & - & - \\ 0.2318 & 0.1748 & 0.2621 & - \end{bmatrix},$$

$$SD_4 = \begin{bmatrix} - & - & - & - \\ 0.3126 & - & 0.1143 & - \\ 0.2239 & - & - & - \\ 0.4527 & 0.2039 & 0.2948 & - \end{bmatrix},$$

$$SD_5 = \begin{bmatrix} - & - & - & - \\ 0.1731 & - & 0.0404 & - \\ 0.1382 & - & - & - \\ 0.2822 & 0.1319 & 0.1670 & - \end{bmatrix}$$

Then, the overall stochastic dominance matrix $SD = [sd_{nq}]_{4\times4}$ is set up as follows.

$$SD = \begin{bmatrix} 0 & 0 & 0.0103 & 0 \\ 0.2593 & 0 & 0.1063 & 0 \\ 0.1826 & 0 & 0 & 0 \\ 0.3966 & 0.1871 & 0.2719 & 0 \end{bmatrix}$$

Finally, according to the overall stochastic dominance degree sd_{nq}, the dominant degree $\phi^+(a_n)$, the non-dominant degree $\phi^-(a_n)$, and the overall relative dominant degree $\phi(a_n)$ for each hotel can be obtained. The results are shown in TABLE 6.

TABLE 6. The evaluation results of the four hotels.

a_n	ϕ^+	ϕ^-	ϕ	Ranking
a_1	0.0026	0.2096	0.2071	4
a_2	0.0914	0.0468	0.0446	2
a_3	0.0457	0.0971	0.0515	3
a_4	0.2139	0.0000	0.2139	1

The ranking result of the overall customer satisfaction obtained by the method proposed by Fan *et al.* is $HI \succ DJ \succ KM \succ FD$, which is the same as the one obtained by the method proposed in this paper. However, Fan *et al.*'s method cannot be used to evaluate customer satisfaction with different attributes. Ranking the overall customer satisfaction alone cannot help the hotel to make targeted satisfaction improvement decisions from the attribute perspective. The method proposed in this paper evaluates the customer satisfaction of each hotel attribute to help the hotel understand its advantages and disadvantages in different attributes to develop specific satisfaction improvement strategies for attributes. Next, the evaluation grades of different websites in our case are the same. However, for the case of inconsistencies in the evaluation grades among websites, the method proposed by Fan *et al.* no longer applies, while the method in this paper does. In addition, the proposed method in this paper determines attribute weights based on online reviews, which is more objective and more suitable for hotel applications than the method proposed by Fan *et al.*

V. CONCLUSION

This paper proposes a method for measuring hotel customer satisfaction considering the reliability of online reviews. This method is based on the D-S evidence theory, and considers comprehensively online evaluation information of multiple online travel review websites. This evaluation information includes online ratings, reviewer level, review time and helpful votes. Based on the collected reviewer level, review time, and helpful votes, online review reliability can be calculated. The basic probability assignments are then obtained through the calculated reliability and online ratings. After that, the various sets of evaluation grades from multiple websites are transformed into a unified set to combine the basic probability assignments by Dempster's rule of combination. The combined probability assignments are used to compute the weights of attributes and then further aggregated to the overall probability assignments. At last, the expected utility is calculated and used to analyze the customer satisfaction of hotels. The major contributions of this paper are discussed as follows.

This paper's proposed method considers the reliability of online reviews, which relates to three aspects, i.e., reviewer level, review time, and helpful votes. Specifically, the higher the reviewer's level, the more abundant his review experience, hence the more reliable his review; the closer the review time is, the more the review conforms to the hotel's actual situation, and the higher the reliability of the review is; the more helpful votes the review obtains, the more consumers approve of the review, and the more reliable the review is.

The proposed method in this paper can be applied to hotel customer satisfaction evaluation based on multi-site online reviews. In reality, there are many online travel review websites, on which a lot of online reviews reflect customer satisfaction with the hotel. However, the evaluation grades are not always the same among websites, which makes it difficult to evaluate hotel customer satisfaction based on multi-site online reviews. In view of the different evaluation grades among websites, this method gives a specific solution. Therefore, the proposed method is more flexible.

Based on the above analysis, this paper has following management implications. On the one hand, the proposed method in this paper can help hotel managers evaluate the overall customer satisfaction and customer satisfaction on various attributes. On the other hand, due to the openness of the Internet, hotel managers can obtain online reviews of competing hotels to employ the method to analyze their customer satisfaction. By comparing with competing hotels, hotel managers can identify the hotel's strengths and weaknesses in different attributes to make targeted decisions about allocating limited resources. In this way, the hotel can increase customer satisfaction and thus improve its competitiveness in the industry.

This paper also has limitations, which may serve as avenues for future research. This paper does not consider the problem of fake reviews. At present, there are indeed cases of posting fake reviews on online review sites, which interfere with customer satisfaction evaluations for a hotel; thus, future research can take into account the impact of fake reviews.

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