Cross-platform hotel evaluation by aggregating multi-website consumer reviews with probabilistic linguistic term set and Choquet integral

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Abstract
In order to adequately utilize and integrate both ratings and comments from multiple websites, this paper proposes a new hotel evaluation model with probabilistic linguistic information processing. Taking consumers’ possible psychological activities when leaving their reviews into consideration, this paper adapts the Weber-Fechner Law with the linguistic scale function and develop a novel unbalanced linguistic scale function. This paper also attempts to develop a method that enables adjusting linguistic-term formations among different websites to make full use of information. Then, we learn the decision criteria and the corresponding weight of hotel evaluation based on analyzing rating rules and consumer comments. Moreover, considering the interrelationships among criteria, this paper extends the Choquet integral to the probabilistic linguistic term set (PLTS) environment and designs some novel fusion operators. Furthermore, considering the fact that different websites mostly focus on heterogeneous hotel criteria, this paper puts forward a weighted averaging linear assignment based ranking method with the aid of PLTS Choquet integral. Finally, a case study of hotel evaluation is given to illustrate the validity and applicability of our proposed approach.

Keyword Hotel evaluation · Multi-website information · Probabilistic linguistic term set · Online reviews · Choquet integral
1 Introduction

1.1 Background and motivation

Using online reviews as a guide of online purchasing has become ubiquitous for customers, where hotel selection could be its typical case. Before the starts of journeys, a great number of customers would use online booking agents such as TripAdvisor and Booking.com to make their hotel reservations. However, on one hand, due to the variety of online reviews, customers would encounter the issue of “information overload”, which hinders them from making proper decisions (Jacoby, 1977). On the other, the uncertainty and fuzziness of online reviews also aggravates customers’ burdens of decision making (Sun et al., 2019). To this regard, a plenty of researches upon hotel evaluation have been made to help customers leverage online reviews as a source of information to improve their ability of decision making.

Generally speaking, the online reviews consist of two sources of information: numerical ratings and textual comments. Accordingly, the current researches shading lights on hotel evaluation methodologies are mainly based on utilizing one of two bases for decision making, namely the level of rating score and the result of comments, respectively. For example, Yu et al. (2018) utilized the rating scores to establish the linguistic distribution assessments for hotels and proposed a multi-criteria decision making method for hotel selection. Zhang et al. (2020) discussed a multi-stage multi-attribute decision making method based on online ratings for hotel selection considering the aspirations with different development speeds. Hu et al. (2017) developed an opinion mining technique based on summarizing online textual comments. Their approach jointly considered author, review time, usefulness, and opinion factors, which can extract more comprehensive hotel information. Nie et al. (2020) proposed an improved sentiment dictionary and an evidence theory-based fusion method to explore a hotel selection model driven by online textual comments. Wang et al. (2021) analyzed the textual comments to identify characteristic preferences among travellers and developed a cloud-based multi-criteria hotel selection model.

Although the existing methodologies have had deep insights upon each part of online reviews, the idea of scrutinizing both ratings and comments is receiving attention in recent years. For example, in the area of product recommendation, Liu et al. (2020) have clarified that ratings and comments are two complementary sources of information. In the area of hotel selection, Zhao et al. (2021) have argued that information integration is supposed to combine both ratings and comments to enhance the robustness. Therefore, it would be beneficial fusing both rating patterns and textual comments to acquire a more comprehensive evaluation for hotels, which needs further investigations.

Obviously, utilizing both ratings and comments for hotel evaluation is intrinsically an approach of multi-source information processing. It utilizes multiple forms of data (numerical and textual) which are exposed by a bag of sensors (previous customers). This idea could be extended when we consider a real-world hotel selection procedure. As is shown in Fig. 1, it is valuable to notice that consumers are likely to search on multiple websites while different websites have different regulations for online reviews (Margaris et al., 2020). Specifically, the criteria set to be rated (let us call them “rating criteria”) on different websites may be differentiated from each other, while the rating scales of criteria could be different as well. To help customers evaluate hotels, the differences among websites are supposed to be analysed (Zhang et al., 2019), i.e., the hotel evaluation should consider the information fusion under a balance among the diversity of websites, the complexity of data, and the timeliness of reviews. The first two are required to tackle the problem caused by sampling...
from multiple sources of information while the last is to maintain the time effectiveness of online reviews for hotel evaluation. Since customers are likely to proceed cross-platform searchings, integrating information from multiple websites also needs further investigations in the area of hotel evaluation.

To specify the mission of developing a hotel evaluation method based on integrating information from multiple websites, let us reconsider a typical customer who enjoys little experience of travel accommodation. This customer is likely to encounter the problem that she could hardly articulate her needs and her concerns about decision criteria (Bond et al., 2008). Under this circumstance, a reasonable strategy she could take into action is reading the evaluations from other customers and trying to derive some critical criteria with their weight information from her own observations. At the same time, the customer may also have concerns about how criteria are interrelated, which will influence her attitude towards the criteria (Li et al., 2013; Wang et al., 2020). Therefore, the hotel evaluation model should consider the following questions, which form the research objects of this paper.

(1) How to find out key criteria that customers are generally concerned about?
(2) How to unify the evaluation information of both ratings and comments?
(3) How to determine weight information of criteria while considering their interrelationships?
(4) By distinguishing properties of different platforms, what should be the method for integrating multi-website information?
(5) According to the analysis of multi-website information, what will be the method of ranking the hotels?

1.2 Contributions to the existing literature

For hotel evaluation, whether using online ratings or comments, from single website or multiple websites, they all require the technique of semantics analysis. It’s important to represent unstructured reviews mathematically (Wu & Liao, 2021). In this regard, the probabilistic linguistic term set (PLTS) theory proposed by Pang et al. (2016) could be an effective tool. The PLTS utilizes linguistic terms which represent linguistic semantics with their corresponding possibilities of being used to fit the situation of group decision making and has been widely adapted to decision making environment such as product selection (Liu & Teng, 2019), system risk management (He et al., 2021) and financial technology selection (Mao et al., 2019). This paper will explore the hotel evaluation in the framework of PLTS theory and characterize customers’ evaluations based on a nine-level semantic system (Saaty, 1980).
In general, the work of this paper takes the novel idea of cross-platform searching as the starting point and scrutinizes a hotel evaluation method based on integrating information from multiple websites with PLTSs. Taking the inherent differences among websites into consideration, we attempt to develop a method that enables adjusting linguistic-term formations among different websites to make full use of information. To determine the weight information of decision criteria, we investigate a pair of probabilistic linguistic entropy and cross-entropy. We further consider the situation that all decision criteria are homogeneously related (Li et al., 2013; Wang et al., 2020), and adapt the fuzzy measure (Sugeno, 1974) with Choquet integral (Choquet, 1953) into the probabilistic linguistic environment. Ultimately, this paper puts forward a weighted averaging linear assignment based ranking method to acquire a compositive ranking result for hotels. In view of the above-mentioned analysis, the main contribution of this paper would be summarized as follows:

(1) This paper proposes a hotel evaluation method for consumers that utilizes both ratings and comments from multiple websites, which extends the hotel evaluation to a cross-platform context.
(2) This paper develops a novel unbalanced linguistic scale function for hotel evaluation by utilizing the Weber-Fechner Law.
(3) This paper puts forward a pair of entropy and cross entropy measure for PLTS and discusses an entropy-based method for determining weight information of decision criteria.
(4) Considering the interrelationships among criteria, this paper extends the Choquet integral to the probabilistic linguistic information processing and develops novel fusion operators.

1.3 Framework of this study

The reminder of this paper is organized as follows: Sect. 2 discusses some essential concepts and relative theories of PLTSs and Choquet integral. Sections 3 and 4 elaborate the hotel evaluation method based on integrating information from multiple websites with PLTSs. The former section illustrates the notations of this work, while the latter section clarifies the process of information collection and integration during the decision making. The five research questions summarized at the end of Sect. 1.1 are tackled by the corresponding subsections in Sect. 4. Our proposed method is then applied to an illustrative example in Sect. 5 with some discussions. In Sect. 6, we conclude the paper and further discuss the limitations of our work to elaborate future studies.

2 Preliminaries

This section discusses basic principles of PLTS theory, linguistic scale function, λ-fuzzy measure and Choquet integral. The content of this section could be the theoretical foundation for appreciating the work of this study.

2.1 PLTS and linguistic scale function

The PLTS theory proposed by Pang et al. (2016) is an extension of the linguistic term set theory (Zadeh, 1975; Zhou & Xu, 2018). A PLTS is constructed to capture decision makers’ preferences by a series of linguistic terms and their corresponding possibilities of being used. Therefore, it can be chosen as a means for characterizing the distribution of evaluation
semantics of a group of people, which fits the context of analyzing online reviews. For more information, readers could refer to Pang et al. (2016) and Lin and Xu (2018).

A linguistic term set is commonly defined as a set: \( S = \{s_i \mid i = -\tau, \ldots, 0, \ldots, \tau\} \), where \( \tau \) is a positive integer. Its element \( s_i \) is called a linguistic term, which expresses a qualitative description of semantics (Farhadinia, 2016). Take a nine-level semantic system (Saaty, 1980) for example, it could be described by a linguistic term set like: \( S = \{s_{-4} = \text{terrible}, s_{-3} = \text{poor}, s_{-2} = \text{worse}, s_{-1} = \text{bad}, s_0 = \text{fair}, s_1 = \text{good}, s_2 = \text{better}, s_3 = \text{great}, s_4 = \text{excellent}\} \). The set is required to be ordered, i.e., \( s_i < s_j \) if \( i < j \). For linguistic decision making, whether from words to words or from words to numerical outputs, the “discrete” linguistic term set will be extended to the “continuous” linguistic term set \( \tilde{S} = \{s_j \mid j \in [-q, q]\} \) where \( q (q > \tau) \) is a sufficiently large positive integer (Xu & Wang, 2017; Lin & Xu, 2018). For convenience, we denote the extended linguistic term set the same as the original linguistic term set, i.e., \( S \). It is also necessary to declare in advance that decision makers are supposed to use the original linguistic terms for expressing their evaluations. The extended linguistic terms are produced by numerical operations.

**Definition 1** (Xu, 2005; Wang et al., 2014) Let \( S \) be an extended linguistic term set based on the original set \( \{s_{-\tau}, \ldots, s_0, \ldots, s_\tau\} \). If \( s_j, s_k \in S \) and \( \theta_1, \theta_2 \in \mathbb{R} \), the linguistic scale function \( f(s_j, S) : s_j \rightarrow \theta \) is defined as a strictly monotonically increasing real function on \( S \) with regard to the subscript \( i \). Since the function \( f \) has its inverse \( f^{-1} \), for any two linguistic terms \( s_\alpha, s_\beta \in S \) and a real number \( \mu \in [0, 1] \), the basic operations of linguistic terms are defined:

\[
\begin{align*}
\alpha \oplus \beta &= f^{-1}(f(\alpha) + f(\beta)) \\
\mu \alpha &= f^{-1}(\mu f(\alpha))
\end{align*}
\]  

(1)

Based on the linguistic term set theory, the PLTS theory was then proposed. Since the traditional definition (Pang et al., 2016) omits the semantic differences among linguistic terms, we suggest the following definition:

**Definition 2** Let \( S = \{s_{-\tau}, \ldots, s_0, \ldots, s_\tau\} \) be an original linguistic term set where \( s_i (i = -\tau, \ldots, 0, \ldots, \tau) \) is a linguistic term. The set

\[
L(p) = \left\{L^{(k)}(p^{(k)}) \mid L^{(k)} = s_{k-1-\tau}, k = 1, 2, \ldots, 2\tau + 1; p^{(k)} > 0, \sum_{k=1}^{2\tau+1} p^{(k)} \leq 1\right\}
\]  

(2)

is defined as a PLTS generated by \( S \). The set is directly written to be ordered that \( \forall k_1 < k_2, L^{(k_1)} < L^{(k_2)} \). Linguistic terms associated with no possibility of being used, i.e., \( p^{(k)} = 0 \), is allowed to be omitted when presenting the set, but will be used for operations. Its element \( L^{(k)}(p^{(k)}) \) is called a probabilistic linguistic term element, which is composed of a linguistic term \( L^{(k)} \) (in \( S \)) and its possibility of being used \( p^{(k)} \). \#\( L(p) = \text{Card}\{L(p)\} \) is the total number of linguistic term elements in the set. If \( \#L(p) = 1 \) and \( p^{(1)} = 1 \), then the PLTS is reduced to a linguistic term.

Apparently, our new definition mainly focuses on linguistic terms’ ordinal relations and considers the possibility information as an affiliated attribute of linguistic terms. Therefore, the DAWA operator (weighted averaging operator of distribution assessments) (Zhang et al., 2014) can be easily adapted to the PLTS environment for information aggregation.

**Definition 3** Let \( L_1(p_1) \) and \( L_2(p_2) \) be two PLTSs generated by the same linguistic term set \( S \), \( w_1, w_2 \in [0, 1] \) be their weight parameters that satisfy \( w_1 + w_2 = 1 \). Then, the DAWA
operator of PLTSs can be defined as:
\[
L_1(p_1) ∪ L_2(p_2) = \left\{ L^{(k)} (w_1 p_1^{(k)} + w_2 p_2^{(k)}) \mid L^{(k)} = s_{k-1-\tau}, k = 1, 2, \cdots, 2\tau + 1 \right\}
\] (3)

Ultimately, by combining the linguistic scale function (Wang et al., 2014) and the work of Pang et al. (2016), we then introduce the comparison method for PLTSs.

**Definition 4** Let \( L(p) \) be a PLTS generated by linguistic term set \( S \), \( f \) is the linguistic scale function of \( S \). \( \#L(p) = \text{Card}\{L(p)\} \). The score function of PLTS is \( E(L(p)) = \frac{\sum_{k=1}^{\#L(p)} f(L^{(k)})p^{(k)}}{\sum_{k=1}^{\#L(p)} p^{(k)}} \), the accuracy function of PLTS is \( \sigma(L(p)) = \sqrt{\frac{\sum_{k=1}^{\#L(p)} [p^{(k)}(f(L^{(k)}) - E(L(p)))^2]}{\sum_{k=1}^{\#L(p)} p^{(k)}}} \).

For any two PLTSs \( L_1(p_1) \) and \( L_2(p_2) \), their comparison is determined by the following rules:

1. If \( E(L_1(p_1)) > E(L_2(p_2)) \), then \( L_1(p_1) > L_2(p_2) \);
2. If \( E(L_1(p_1)) < E(L_2(p_2)) \), then \( L_1(p_1) < L_2(p_2) \);
3. If \( E(L_1(p_1)) = E(L_2(p_2)) \), then,
   
   (i) If \( \sigma(L_1(p_1)) > \sigma(L_2(p_2)) \), then \( L_1(p_1) < L_2(p_2) \);
   
   (ii) If \( \sigma(L_1(p_1)) < \sigma(L_2(p_2)) \), then \( L_1(p_1) > L_2(p_2) \);
   
   (iii) If \( \sigma(L_1(p_1)) = \sigma(L_2(p_2)) \), then \( L_1(p_1) = L_2(p_2) \).

### 2.2 \( \lambda \)-Fuzzy measure and Choquet integral

The rise of the fuzzy set theory (Zadeh, 1965) lighted a path which extended the traditional measure theory. In the year of 1974, Sugeno (1974) proposed a novel set function called “fuzzy measure” which did not satisfy the additivity but held the weak monotonicity and the weak continuity. The fuzzy measure is defined as follows (Sugeno, 1974, 1977):

**Definition 5** A fuzzy measure on a set \( X \) is a function \( \mu : \mathcal{P}(X) \rightarrow [0, 1] \) satisfying the following conditions:

1. (Boundary condition) \( \mu(\emptyset) = 0, \mu(X) = 1 \);
2. (Monotonicity condition) If \( C, D \in \mathcal{P}(X) \) and \( C \subseteq D \), then \( \mu(C) \leq \mu(D) \).

To calculate the fuzzy measure among the criteria sets, Sugeno (1977) then proposed the \( \lambda \)-fuzzy measure:

\[
\mu(C \cup D) = \mu(C) + \mu(D) + \lambda \mu(C)\mu(D), \; \lambda \in (-1, +\infty), \; \forall C, D \in \mathcal{P}(X), \; C \cap D = \emptyset \)
\] (4)

where \( \lambda \) reflects the interaction between criteria. Roughly speaking, \( \lambda \) has three cases, i.e., \( \lambda = 0, \lambda < 0 \) and \( \lambda > 0 \). For \( \lambda = 0, \lambda < 0 \) and \( \lambda > 0 \), the \( \lambda \)-fuzzy measure becomes an additive measure, an sub-additive and an super-additive measure, respectively. If \( X \) is finite, then the \( \lambda \)-fuzzy measure satisfies the following equation:

\[
\mu(X) = \frac{1}{\lambda} \left\{ \prod_{i=1}^{n} [1 + \lambda \mu(x_i)] - 1 \right\}, \; \lambda \neq 0
\] (5)

Since \( \mu(X) = 1 \), we can rewrite (5) as:

\[
\lambda + 1 = \prod_{i=1}^{n} [1 + \lambda \mu(x_i)] \tag{6}
\]
Further, for any subset $C \in \mathcal{P}(X)$, we have:

$$\mu(C) = \begin{cases} \frac{1}{\lambda} \left\{ \prod_{x_i \in C} [1 + \lambda \mu(x_i)] - 1 \right\}, & \text{if } \lambda \neq 0; \\ \sum_{x_i \in C} \mu(x_i), & \text{if } \lambda = 0. \end{cases}$$  \tag{7}$$

The fuzzy measure is a powerful tool for characterizing interrelationships among the criteria in real decision making problems, and Choquet integral (Choquet, 1953) could be its reliable assistance when conducting information aggregation (De et al., 2000). The Choquet integral based on fuzzy measure is defined as follows (Choquet, 1953; Wang & Klir, 1992):

**Definition 6**  Let $g$ be a real-valued function on a fixed set $X = \{x_1, x_2, \cdots, x_n\}$, $\mu$ be a fuzzy measure on $X$, the Choquet integral of $g$ with respect to $\mu$ is defined as:

$$\int g \, d\mu = \sum_{i=1}^{n} [\mu(X_{(i)}) - \mu(X_{(i+1)})] g(x_{(i)})$$ \tag{8}$$

where the parentheses used for indices represent a permutation on $X$ according to a monotonic order that $g(x_{(1)}) \leq \cdots \leq g(x_{(n)})$, $X_{(i)} = \{x_{(i)}, \cdots, x_{(n)}\}$, and $X_{(n+1)} = \emptyset$.

3 Notations

The mathematical notations mainly used in the following Sect. 4 and their corresponding meanings are summarized in the following Table 1:

4 Modeling hotel evaluation method with PLTS theory

This section elaborates our hotel evaluation model. We will start with the data collection and criteria determination process (Sect. 4.1), which mainly answers the research question (1). By unifying evaluation information with PLTS theory (Sect. 4.2), we then discuss an entropy-based method to calculate weight information of decision criteria (Sect. 4.3), which mainly answers the research question (2) and (3). After obtaining the structured information, the probabilistic linguistic Choquet integral is introduced to aggregate the evaluations (Sect. 4.4), which mainly answers the research question (4). Ultimately, we design a weighted averaging linear assignment model for hotel ranking (Sect. 4.5), which mainly answers the research question (5). The proposed hotel evaluation model is further extended in Sect. 4.6 to address the problem that rating details may not be displayed by the websites.

4.1 Collecting data and finding decision criteria

As we discussed before, multiple websites will generate multi-source information. Therefore, the set of decision criteria should be determined by analyzing evaluations from all the websites. Take the website $P_j$ for example, its rating criteria are given by the website itself. These rating criteria are officially issued and can reflect some perceptions from the operations team, which could provide a distinct direction to customers. Apart from that, topics that are frequently mentioned in comments (let us call them “comment criteria”) could also be
informative. These topics reflect the group preference of customers to some extent. By combining rating criteria and comment criteria, we can then deduce the criteria that customers are concerned about. The criteria recognition of ratings is straightforward, while the recognition of comments could be done with the aid of sentence-constrained topic models (Büschken & Allenby, 2016). Specifically, the data collection and preprocessing will be conducted through the following steps:

**Step 1** Use crawler software to obtain reviews (bundles of ratings and comments in a certain time range) from all websites. The $l^{th}$ review for hotel $A_i$ on platform $P_j$ is denoted

| Classes        | Notations | Meanings |
|----------------|-----------|----------|
| **Entity notations** | $A$ | The set of hotels that are about to be evaluated. |
|                | $A_i$ | The $i^{th}$ hotel in set $A$. In total, $m$ hotels. |
|                | $P$ | The set of websites that will be used for searching. |
|                | $P_j$ | The $j^{th}$ website in set $P$. In total, $n$ websites. |
| **Criteria notations** | $C_j$ | The set of decision criteria obtained from website $P_j$. |
|                | $c_{j,k}$ | The $k^{th}$ criterion in set $C_j$. In total, $\Delta_j$ criteria. |
|                | $C$ | The set of decision criteria obtained from all $n$ websites. |
|                | $c_k$ | The $k^{th}$ criterion in set $C$. In total, $\Delta$ criteria. |
| **Evaluation notations** | $r_{j,l}^i$ | The $l^{th}$ review for hotel $A_i$ on website $P_j$. |
|                | $\rho_{j,l,k}^i$ | The standardized evaluation semantics for hotel $A_i$ under criterion $c_k$ obtained from review $r_{j,l}^i$ on website $P_j$. |
|                | $\delta_{j,l,k}^i$ | The density of the review $r_{j,l}^i$ with respect to the criterion $c_k$. |
|                | $E_{j,k}^i$ | The overall emotional tendency of evaluations for hotel $A_i$ on website $P_j$ with respect to the criterion $c_k$. |
|                | $L_{j,k}^i$ | The evaluation PLTS for hotel $A_i$ on website $P_j$ with respect to the criterion $c_k$. |
|                | $L_j^i$ | The hotel $A_i$’s overall evaluation on the website $P_j$. |
| **Model notations** | $\mathcal{E}(L(p))$ | The entropy of PLTS $L(p)$. |
|                | $\mathcal{E}_s(c_{j,k})$ | The standardized entropy of criterion $c_{j,k}$. |
|                | $\mathcal{E}(L_1(p_1), L_2(p_2))$ | The cross-entropy of two PLTSs $L_1(p_1)$ and $L_2(p_2)$. |
|                | $\mathcal{E}_s(c_{j,k})$ | The standardized cross-entropy of criterion $c_{j,k}$. |
|                | $\lambda_j$ | The parameter of $\lambda$–fuzzy measure for website $P_j$. |
|                | $\mu(c_{j,k})$ | The fuzzy measure of criterion $c_{j,k}$. |
|                | $\theta_i = f(s_i)$ | The novel linguistic scale function based on the Weber-Fechner Law. |
|                | $F$ | The ranking matrix of hotels. |
|                | $\Pi$ | The weighted averaging ranking matrix of hotels. |
|                | $M$ | The extended weighted averaging ranking matrix of hotels. |
as $r_{j,l}$. For example, as is shown in Fig. 2, an online evaluation is typically constructed by five parts of information, namely “basic user information”, “average rating score”, “comment texts”, “accommodation information”, and “details of rating”. The “details of rating” and the “comment texts” are selected to form $r_{j,l}$. We must notice that the average rating score is automatically calculated by the website itself and is compelled to be displayed. However, the accommodation information are generally incomplete and in some common cases, the details of rating may also be invisible. These kinds of predicaments could provide us little help and are not our focus here.

**Step 2** Preprocessing the texts: word segmentation and removing the stop words. Utilize text mining algorithm or software to discover latent topics inside the comments. Then we conduct a frequency analysis to find out those criteria that customers generally concern. We combine them with the rating criteria, denote the set of criteria mentioned by $P_j$ as $C_j$. Then denote the set of decision criteria as $C = \bigcup_j C_j = \{c_1, c_2, \ldots, c_\Delta\}$.

**Step 3** According to the results derived from Step 2, we extract evaluation information from ratings and comments. The standardized evaluation semantics for hotel $A_i$ under criterion $c_k$ obtained from review $r_{j,l}$ on platform $P_j$ is denoted as $\rho_{j,l,k}$. We restrict that $\rho_{j,l,k} \in [-1, 1]$. For ratings, this could be achieved according to the original rating scale of each website. For comments, as is suggested by Liu and Teng (2019), we utilize natural-language-processing algorithms to analyze the sentiment and derive its value of emotional tendency. There exists such a situation that the ratings and comments bundled under the same customer mention the same criterion. Under this circumstance, we must scrutinize a balance of information under that criterion. For example, we can consider that the customer rates and comments upon the same criterion is mainly due to her dissatisfaction to the rating result which is only displayed as a certain number. Therefore, it is acceptable to reserve only the data of comments. The purpose of this operation is to guarantee the uniqueness of customers’ evaluations, i.e., one
customer on one platform is ultimately supposed to give non-repetitive evaluations about one certain hotel upon each criterion.

4.2 Unifying evaluation information with PLTS

Different websites can be considered as independent sensors, as customers on one website may reach consensus on a number of evaluations about a certain hotel in some extent, which differentiates among websites. On the one hand, customers who hold priors of accommodation would like to evaluate the hotel by comparing it with their past experiences (Chow et al., 1995). On the other, those who lack of prior information are able to roughly recognize the quality of hotels through social learning (Ifrach et al., 2019) and then evaluate their experiences based on it. Therefore, the cross-platform searching will lead to a conflict between personal viewpoints and group viewpoints, and also a conflict among information from different websites. To handle it, our central idea is balancing the evaluation semantics on each website with respect to each criterion when that criterion is considered by those websites.

According to Liu and Teng (2019), after obtaining the evaluation semantics \( \rho_{j,l,k}^i \), if \( \rho_{j,l,k}^i \in [-1, -0.75) \), then the evaluation is supposed to be classified as \( s_{-4} \); if \( \rho_{j,l,k}^i \in [-0.75, -0.5) \), then the evaluation is supposed to be classified as \( s_{-3} \); similarly, for \( \rho_{j,l,k}^i \) inside the interval \([ -0.5, -0.25), [-0.25, 0), (0,0.25), (0.25,0.5], (0.5,0.75) \), and \([0.75,1) \), the evaluation should be classified as \( s_{-2}, s_{-1}, s_1, s_2, s_3 \), and \( s_4 \) respectively. Specifically, the evaluation of \( \rho_{j,l,k}^i = 0 \) is classified as \( s_0 \). Obviously, this rule is not flexible for the current multi-website context. In the following, we will discuss a novel method of transforming evaluation information into PLTSs by determining the transformation rules for each website with respect to each criterion separately. The aim of this procedure is to tackle the information diversity of websites.

Technically, the semantics of a sentence is characterized by its topic and its value of emotional tendency, which are calculated through some natural language processing models. Sentences may share similar semantics if they are about the same topic while their emotional tendencies are numerically close. Thus, based on the idea of clustering, we introduce the concept of support and density for semantics of sentences.

**Definition 7** For a given sentence \( t_0 \) and another sentence \( t \) which are about the same topic, we denote their emotional tendencies as \( p_0 \) and \( p \) respectively, \( p_0, p \in [-1,1] \). Considering a parameter \( d, d \in [0, 1] \), if \(|p - p_0| \leq d \), then \( t \) is defined to be a support of \( t_0 \) with the parameter \( d \), or in short, \( t_0 \)'s support, which means that the semantics of \( t \) is closed to the semantics of \( t_0 \).

**Definition 8** Denote a series of sentences under the same topic as \( T = \{ t_1, t_2, \cdots, t_x \} \). Their emotional tendencies are calculated to be \( p_0, p_1, \cdots, p_x \). Give a parameter \( d, d \in [0, 1] \). For \( t_k \in T \), we denote the number of its support(s) in \( T \) as \( \hat{s}_k \), \( \hat{s}_k = \text{Card}(\{ t \mid |p - p_k| \leq d \}) \). Then, \( \delta_k = \hat{s}_k + 1 \) is defined as the density of \( t_k \) in \( T \) with the parameter \( d \), or in short, \( t_k \)'s density in \( T \).

As is shown in Fig. 3, four sentences are marked by their emotional tendencies along the axis. For a given parameter \( d \) and a selected sentence \( t_0 \), sentences that marked by solid dots are the supports of \( t_0 \) while the sentence marked by a hollow triangle is not. The concept of support and density is associated with the parameter \( d \). The evaluation of high density is representative, and should be considered more important in a group of evaluations.
Take the website $P_j$ for example, we denote its overall emotional tendency of evaluations upon the hotel $A_i$ under the criterion $c_k$ as $E_{i,k}^j$. It is calculated by:

$$E_{i,k}^j = \frac{\sum_l \delta_{j,l,k}^i \rho_{j,l,k}^i}{\sum_h \delta_{j,k}^i \rho_{j,k}^i}$$

(9)

where $\rho_{j,l,k}^i$ presents the emotional tendency of the part of $A_i$'s $l$th evaluation exhibited by $P_j$ that mentions $c_k$. $\delta_{j,l,k}^i$ is the density of that $l$th evaluation among all other evaluations that are about $c_k$.

For a certain criterion $c_k$ that evaluates a certain hotel $A_i$, if it is generally concerned by customers on multiple websites while they differ on its evaluation, then it is reasonable to determine the rule of semantics division for each website respectively. Let us assume that for the hotel $A_i$, customers on the websites $P_k = \{P_1, \cdots, P_t\}$ all concern about the criterion $c_k$. By utilizing the Eq. (9), we can calculate their emotional tendencies to be $E_{i,k}^1, \cdots, E_{i,k}^t$. Take the worst result $E_{i,k}^{-}$ as the negative ideal point and the best result $E_{i,k}^{+}$ as the positive ideal point so that all evaluations satisfy the condition of $E_{i,k}^j \in [E_{i,k}^{-}, E_{i,k}^{+}]$. Thus, we calculate their weighted arithmetic mean $E_{o,k}^j$ as follows:

$$E_{o,k}^j = \frac{\sum_{P_j \in P_k^e} \sum_{P_h \in P_k^e} n_{j,k}^{j,h} E_{j,k}^j}{\sum_{P_h \in P_k^e} n_{h,k}^{j,h}}$$

(10)

where $n_{j,k}^{j,h}$ is the total number of evaluations about $A_i$ under $c_k$ on $P_j$. Based on the results of (9) and (10), we can then deduce a method of semantics division by adjusting the basic division for each website.

The main idea of adjustment is that if evaluations on a website deviate the average and approach the pole, then the customers may suspect whether the benchmarks used by customers on that website differ from other websites and reform their convictions about the information from it. In practice, we calculate the deviation between $E_{j,k}^i$ and the average $E_{o,k}^i$ as follows:

$$d_{j,k}^i = E_{j,k}^i - E_{o,k}^i$$

(11)

Then, the deviation between $E_{j,k}^i$ and the pole $E_{-k}^i$, the deviation between $E_{j,k}^i$ and $E_{+k}^i$ are computed as follows:

$$d_{-k}^i = E_{-k}^i - E_{o,k}^i$$

(12)

$$d_{+k}^i = E_{+k}^i - E_{o,k}^i$$

(13)

In this paper, the method of characterizing customer’s psychological behavior is chosen to be the negative exponential function due to its decay property. Since customers are likely to select the neutral evaluation $s_0$ as their reference point of distinguishing positive and negative
comments, the adjustment can be started up from calculating the value of neutral emotional tendency.

1. If $d_{j,k}^d < 0$, then customers may consider that $P_j$ is strict in evaluation. Therefore, the shift of neutral point in the worst situation could be determined as:

$$\nabla \left( d_{-,-,k}^i \right) = \frac{1}{2} e^{d_{-,-,k}^i}$$

where $t$ is a parameter given in advance. With the increase of $|d_{-,-,k}^i|$, the emotional tendency of evaluation is getting closer to the average, therefore:

$$\nabla \left( d_{-,,-,k}^i \right) = \frac{1}{2} e^{-d_{-,,-,k}^i} d_{-,,-,k}^i, \quad d_{-,,-,k}^i < 0$$

In conclusion, the value of neutral emotional tendency of $A_i$’s evaluation under $c_k$ on $P_j$ that might be recognized by customers is changed from 0 to $\frac{1}{2} e^{-d_{-,,-,k}^i} d_{-,,-,k}^i$.

2. If $d_{j,k}^d > 0$, then customers may consider that $P_j$ is somehow lenient in evaluation. Similarly, the shift is computed as follows:

$$\nabla \left( d_{j,k}^i \right) = \frac{1}{2} e^{d_{j,k}^i}$$

where $t$ is a parameter given in advance. The result is that the value of neutral emotional tendency of $A_i$’s evaluation under $c_k$ on $P_j$ that might be recognized by customers is changed from 0 to $\frac{1}{2} e^{-d_{j,k}^i} d_{j,k}^i$.

3. If $d_{j,k}^d = 0$, then we keep the original reference point 0.

After the calculation of neutral reference point, the other endpoints of sentiment intervals are then determined successively. Decision makers could consult the normal distribution (Pei & Zheng, 2017) or other methods. In this paper, we uniformly distributed other points respectively according to the suggestion of Liu and Teng (2019). An illustrative example of shifting sentiment intervals is presented in Fig. 4, where the parameters are chosen to be $t = 4, d_{1,k}^d = -0.2$. In this figure, $(t)$ and $(\pi)$ give the endpoints of sentiment intervals: $(t)$ presents the basic division, which is uniformly distributed, while $(\pi)$ presents the division result after the shift of reference point $s_0$. Ultimately, we calculate the frequency of each linguistic term and construct the PLTS $L_{j,k}^i$ by PLTS theory. To capture the uncertainty of semantics, we introduce a relatively new method that classifies a semantics into two adjacent linguistic terms according to its value of emotional tendency. If $\rho_{j,i,k}^j$ is located inside the interval of two linguistic terms $s_i$ and $s_{i+1}$, then we have: the distance between $s_i$ and $s_{i+1}$ is $d_s$, the distance between $\rho_{j,i,k}^j$ and $s_i$ is $d_-$, and the distance between $\rho_{j,i,k}^j$ and $s_{i+1}$ is $d_+$. Then,

$$p_− = 1 - \frac{d_-}{d_s}$$

$$p_+ = 1 - \frac{d_+}{d_s}$$

Thus, $\rho_{j,i,k}^j$ is classified as $s_i$ with a weight of $p_−$ and $s_{i+1}$ with the weight of $p_+$. For example, in Fig. 4, $\rho = 0.3725$ is counted as 0.5 $s_1$ and 0.5 $s_2$ in $(t)$ while 0.3 $s_1$ and 0.7 $s_2$ in $(\pi)$.
4.3 The determination of weight information of decision criteria

The weight information of decision criteria plays an critical role in multi-criteria decision making (Zhang et al., 2021). However, due to the time pressure and the lack of knowledge, a new customer must face the issue that she probably has completely unclear visions about decision criteria. Fortunately, the entropy and cross-entropy could provide assistances to find out which criterion is important (Jaynes, 1957). Frankly speaking, the entropy is the measure of information fuzziness and uncertainty and the cross-entropy is mainly used to measure the discrimination information. They provide an approach for measuring the amount of information. Criteria that could present larger amount of information should be considered more important. Furthermore, in the hotel evaluation model, criteria may interrelated with each other (Chow et al., 1995). According to Liang et al. (2019) and Cui and Zhao (2020), we can utilize the entropy and cross-entropy to derive the fuzzy measures. Therefore, in this paper, we will mainly define a pair of entropy and cross-entropy measures for PLTSs and then use them to determine the fuzzy measures.

**Definition 9** For a given linguistic term set $S = \{s_{-\tau}, \cdots, s_0, \cdots, s_{\tau}\}$, let $L(p)$ be a PLTS generated by $S$. The entropy of $L(p)$ is defined as:

$$E(L(p)) = -\frac{1}{\ln(2\tau + 1)} \sum_{p^{(k)}>0} p^{(k)} \ln p^{(k)}$$  \hspace{1cm} (19)

**Proposition 1** The entropy of $L(p)$ is a real-valued function $\mathcal{E}: L(p) \rightarrow [0, 1]$ that satisfies the following conditions:

1. $\mathcal{E}(L(p)) = 0$ iff $\exists p^{(k)} = 1$. Under this circumstance, the PLTS is reduced to a single linguistic term.
2. $\mathcal{E}(L(p)) = 1$ iff $\forall k \in [1, 2\tau + 1], p^{(k)} = \frac{1}{2\tau + 1}$.

Proposition (1) assumes that the information presented by a single linguistic term is certain, which seems to have a conflict with the property of linguistic terms (Farhadinia, 2016). However, under the environment of PLTS, what provides information in reality are the ordinal relations of different linguistic terms and terms’ possibilities of being used. Therefore, the fuzziness of linguistic term itself is not so informative. Proposition (2) suggests that only when the PLTS is uniformly distributed, the entropy of the set can reach its maximum.
Under our decision scenario, the standardized entropy of criterion \( c_{j,k} \) will be:

\[
E_s(c_{j,k}) = \frac{1}{m} \sum_i E\left(L_{j,k}^i\right)
\]  

(20)

**Definition 10** Let \( L_1(p_1) \) and \( L_2(p_2) \) be two PLTSs generated by the same linguistic term set \( S \). Their cross-entropy is defined as:

\[
C(L_1(p_1), L_2(p_2)) = -\sum_{k=1}^{2\tau+1} \tilde{p}_1^{(k)} \ln \tilde{p}_2^{(k)}
\]

(21)

where \( \tilde{p}_i^{(k)} = \frac{\exp p_i^{(k)}}{\sum_i \exp p_i^{(k)}} \) is the softmax function of \( p_i^{(k)} \), the linguistic term \( L_i^{(k)} \)'s possibility of being used in set \( L_i(p_i) \).

Under our decision scenario, the standardized cross-entropy of criterion \( c_{j,k} \) will be:

\[
E_s(c_{j,k}) = \frac{1}{1 + e^{-E(c_{j,k})}}
\]

(22)

where \( E(c_{j,k}) = \frac{E(c_{j,k}) - \text{mean}(E(c_{j,k}))}{\text{std}(E(c_{j,k}))} \), \( E(c_{j,k}) = \sum_i \sum_{t \neq k} E\left(L_{j,k}^i, L_{j,t}^i\right) \), and \( \text{mean}(E(c_{j,k})) \), \( \text{std}(E(c_{j,k})) \) is the arithmetic mean and standard deviation of \( E(c_{j,k}) \) on website \( P_j \) respectively. According to the results of Liang et al. (2019) and Cui and Zhao (2020), the combination entropy \( \omega \) could be used as the fuzzy measure of criteria. Hence, we have:

\[
\mu(c_{j,k}) = \omega = 1 - \frac{1}{2} \left[ E_s(c_{j,k}) + E_s(c_{j,k}) \right]
\]

(23)

Obviously, \( \mu(c_{j,k}) \in (0, 1) \). By combining the results of (6) and (23), we can obtain \( \lambda_j \) for each website as follows:

\[
\lambda_j + 1 = \prod_{c_{j,k} \in C_j} \left[ 1 + \lambda_j \mu(c_{j,k}) \right]
\]

(24)

Then, by utilizing (7), we further calculate the fuzzy measure on each combination of criteria \( R_j \) for each website:

\[
\mu(R_j) = \begin{cases} 
\frac{1}{\sum_{c_{j,k} \in R_j} \mu(c_{j,k})} \left( \prod_{c_{j,k} \in R_j} [1 + \lambda_j \mu(R_j)] - 1 \right), & \text{if } \lambda_j \neq 0; \\
\sum_{c_{j,k} \in R_j} \mu(c_{j,k}), & \text{if } \lambda_j = 0.
\end{cases}
\]

(25)

### 4.4 Information integration with probabilistic linguistic Choquet integral

Since the decision criteria used by different websites are differentiated from each other, a moderate idea of information integration is that the information is supposed to be initially integrated inside each website respectively. In this section, we introduce the probabilistic linguistic Choquet integral based on an improved linguistic scale function and probabilistic linguistic DAWA operator.
Definition 11 Let $L$ be a probabilistic linguistic evaluation on $X$, $\mu$ be a fuzzy measure on $X$, the probabilistic linguistic Choquet integral of $L$ with respect to $\mu$ is defined as:

$$\int L \, d\mu = \bigoplus_{i=1}^{n} \left[ \mu(X_{(i)}) - \mu(X_{(i+1)}) \right] L(x_{i})$$

(26)

where the parentheses used for indices represent a permutation on $X$ according to a monotonous order that $L(x_{(1)}) \leq \cdots \leq L(x_{(n)})$, $X = \{x_{(i)}, \cdots, x_{(n)}\}$, and $X_{(n+1)} = \emptyset$. $\bigoplus$ is the symbol of probabilistic linguistic DAWA operator.

To rank PLTSs, the law of comparison for PLTSs (Definition 4) has pointed out the usage of linguistic scale function which could amplify the differences among linguistic terms. Therefore, it is necessary to set up a function that is able to handle the change of emotions, i.e., the change of customers psychological behaviors. The Weber-Fechner Law is a wildly adapted theory that describes the psychological reactions of humans receiving outside stimulus. It suggests that the threshold of discrimination between two stimuli increases linearly with stimulus intensity which is scaled into a logarithmic internal (Dehaene, 2003). By adapting Weber-Fechner Law into the linguistic scale function, we propose the following function:

$$\theta_i = f(s_i) = \begin{cases} a^i - 1, & i \geq 0; \\ -\alpha^{-\frac{i+\tau}{\tau}} (a^{-i} - 1), & i < 0. \end{cases}$$

(27)

where the parameter $-\alpha^{-\frac{i+\tau}{\tau}}$ is an amplifying ratio which distinguishes the positive term from the negative term. As is suggested by Wang et al. (2014), the base number $a$ could be calculated through $2^{\tau+1}/\sqrt{9}$. Figure 5 shows the sketch map of Eq. (27) with the parameters $\alpha = 1.5$, $a = \sqrt[9]{9}$. The horizontal axis $(i)$ exhibits the balanced linguistic term distribution of a nine-level semantic system, while the vertical axis $\theta_i$ exhibits the unbalanced semantic differences among linguistic terms characterized by the linguistic scale function. For Fig. 5, we can see from the axis on the right side that the discrimination between adjacent linguistic terms are unbalanced.

Based on the above-mentioned discussions, we can then deduce the method of information integration. According to the results of Sect. 4.2, we can construct the decision matrix as $D_{ij,k} = \left[ L_{ij,k}^{j} \right]_{m \times \Delta_j}$. According to the results of Sect. 4.3, by utilizing the Eq. (23), we can derive the vector of fuzzy measures:

$$w_j = [\mu(c_{j,1}), \mu(c_{j,2}), \cdots, \mu(c_{j,\Delta_j})]$$

(28)

Then, we utilize the Eq. (24) to calculate the correlation parameter $\lambda_j$ for each website.

By utilizing the law of comparison for PLTSs (Definition 4 and the Eq. (27)), we rank the PLTSs of evaluations about each hotel on each website:

$$L_{ij,(1)}^{j} \leq L_{ij,(2)}^{j} \leq \cdots \leq L_{ij,(\Delta_j)}^{j}$$

Then, we calculate the fuzzy measures for combinations of criteria based on this ranking series. By utilizing the Eq. (25), we then have:

$$\mu_{ij}^{j} = [\mu(C_{j,(1)}), \mu(C_{j,(2)}), \cdots, \mu(C_{j,(\Delta_j)})]$$

(29)

where $C_{j,(k)} = \{c_{j,(k)}, \cdots, c_{j,(\Delta_j)}\}$. 
By utilizing the Eq. (30), we can obtain the hotel $A_i$’s overall evaluation on the website $P_j$ as follows:

$$L^i_j = \int L^i_{j,k} \, d\mu_j = \frac{\Delta_j}{k=1} \left[ \mu \left( C^i_{j,(k)} \right) - \mu \left( C^i_{j,(k+1)} \right) \right] L^i_{j,(k)} \quad (30)$$

4.5 Ranking hotels with weighted averaging linear assignment model

The results of Sect. 4.4 are the overall evaluation of the hotel $A_i$ obtained on the website $P_j$. In this section, our mission is to integrate information from all the websites. Inspired by the results of Chen (2014), we adapt the weighted averaging linear assignment model to rank hotels across the board.

Initially, by utilizing Definition 4, we can deduce the ranking results of hotels on all the websites. The ranking matrix $F$ is constructed as:

$$F = \begin{bmatrix}
1^{st} & 2^{nd} & \cdots & m^{th} \\
A_1 & F_{11} & F_{12} & \cdots & F_{1m} \\
A_2 & F_{21} & F_{22} & \cdots & F_{2m} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & F_{m1} & F_{m2} & \cdots & F_{mm}
\end{bmatrix} \quad (31)$$

where $F_{ig}$ is the frequency of all circumstances that $A_i$ is ranked the $g^{th}$ position on all websites. We denote $P_{ig} = \left\{ P^i_{g1}, P^i_{g2}, \cdots, P^i_{gF_{ig}} \right\}$ as the set of websites where $A_i$ obtains the $g^{th}$ rank (the total number of websites fitting this request is $F_{ig}$). Note that under the same website, two or more hotels may acquire the same ranking. As is suggested by Chen (2014),
the initial ranking must be separated into equalized rankings when the alternatives are tied in regard to a specific criterion. Therefore, if there are $\pi$ hotels are tied on one website, then the ranking result should be separated into $\pi!$ equalized rankings and each of these equalized rankings is weighted $\frac{1}{\pi!}$. For example, if the ranking result of $A_1, A_2, A_3$ on one website is $(A_1 \sim A_2) > A_3$, then the ranking is supposed to be separated as $A_1 > A_2 > A_3$ and $A_2 > A_1 > A_3$. In this case, both of them are weighted $\frac{1}{2}$. After the separation, the ranking matrix $F$ is then transformed into the weighted averaging ranking matrix $\Pi$:

$$\Pi = \begin{bmatrix}
1^{st} & 2^{nd} & \cdots & m^{th} \\
A_1 & \Pi_{11} & \Pi_{12} & \cdots & \Pi_{1m} \\
A_2 & \Pi_{21} & \Pi_{22} & \cdots & \Pi_{2m} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & \Pi_{m1} & \Pi_{m2} & \cdots & \Pi_{mm}
\end{bmatrix}$$ (32)

Accordingly, $P_{ig}$ is then extended to $P'_{ig}$. We denote the number of total evaluations on $P_j$ as $N_j$, then, $\Pi_{ig}$ is calculated by the following Eq. (33):

$$\Pi_{ig} = \sum_{P_j \in P'_{ig}} N_j \pi_{jg} / \sum_h N_h$$ (33)

where $\pi_{jg}$ records the number of hotels that are tied on $P_j$. Finally, according to the weighted averaging ranking matrix $\Pi$, we establish the linear assignment model (34) as follows:

$$\begin{align*}
\max & \sum_{i=1}^m \sum_{g=1}^m \Pi_{ig} \cdot x_{ig} \\
\text{s.t.} & \begin{cases}
\sum_{g=1}^m x_{ig} = 1, & i = 1, 2, \ldots, m, \\
\sum_{i=1}^m x_{ig} = 1, & g = 1, 2, \ldots, m, \\
x_{ig} = 0 \text{ or } 1, & \forall i, g.
\end{cases}
\end{align*}$$ (34)

By solving the model, we find that if $x_{ig} = 1$, then it shows that the overall ranking of the hotel $A_i$ is $g$. For clarity, Fig. 6 summaries the procedure of hotel evaluation method based on integrating information from multiple websites with PLTSs in detail.

4.6 Model extension

It seems that in reality a phenomenon is rising recently that customers can read only the overall ratings and the written contents of some certain hotels from travel agents, which may hinder them from acquiring sufficient information. Although our proposed method can be reduced to fit the situation, for a further discussion, we then organize an extended model which considers overall ratings as an source of prior information in this section.

Although those details of ratings are invisible for customers who are searching for online reviews of hotels, the average rating scores presented by the website itself could still provide them some prior information. To make full use of data, the customer could directly carry out a TOPSIS method (Hwang & Yoon, 1981) based on the rating criteria and average rating scores to obtain a prior ranking for hotels on each website, and then combine it with the ranking results derived from text analyses to determine a compositive analysis.

Take the website $P_j$ for example, we denote the rating criteria of it as $C_j = \{\overline{c}_{j,1}, \overline{c}_{j,2}, \ldots, \overline{c}_{j,\nu_j}\}$, $\overline{C}_j \subseteq C$. The average rating scores of the hotel $A_i$ on $P_j$ under
$\bar{C}_j$ are denoted as $Z^i_j = \{z_{j,1}^i, z_{j,2}^i, \cdots, z_{j,\nabla_j}^i\}$. Since all criteria are supposed to be beneficial in reality, the decision matrix will be constructed as:

$$Z_j = \begin{bmatrix}
  z_{j,1}^1 & z_{j,2}^1 & \cdots & z_{j,\nabla_j}^1 \\
  z_{j,1}^2 & z_{j,2}^2 & \cdots & z_{j,\nabla_j}^2 \\
  \vdots & \vdots & & \vdots \\
  z_{j,1}^m & z_{j,2}^m & \cdots & z_{j,\nabla_j}^m
\end{bmatrix} \quad (35)$$

Based on the decision matrix, search for the positive ideal point $Z^+_j$ and the negative ideal point $Z^-_j$ by the following formula:

$$Z^+_j = \left\{ \max_i \{z_{j,k}^i\} \mid k = 1, 2, \cdots, \nabla_j \right\} \quad (36)$$

$$Z^-_j = \left\{ \min_i \{z_{j,k}^i\} \mid k = 1, 2, \cdots, \nabla_j \right\} \quad (37)$$

Then, we calculate the distance between hotel $A_i$’s evaluation $Z^i_j$ and the ideal points $Z^+_j$ and $Z^-_j$ respectively:

$$D(Z^i_j, Z^+_j) = \sum_{k=1}^{\nabla_j} \overline{w}_{j,k} |z_{j,k}^i - z_{j,k}^+| \quad (38)$$

$$D(Z^i_j, Z^-_j) = \sum_{k=1}^{\nabla_j} \overline{w}_{j,k} |z_{j,k}^i - z_{j,k}^-| \quad (39)$$

The weight of criterion $\overline{w}_{j,k}$ can be decided by customer herself if she holds at least some priors about travelling, or can be acquired by methodologies such as traditional entropy method (Jaynes, 1957). It can also be given according to the type of traveller, which requests
further investigations upon customers. For example, Wang et al. (2020) pointed out that business travellers may concern more about price and value of money, family travellers may consider the comfort of hotel be more important than other criteria.

In general, the smaller $D(Z^i_j, Z^+_{j})$ and bigger $D(Z^i_j, Z^-_{j})$ the better the alternative. Thus, we further calculate the relative closeness utilizing the following formula:

$$R^i_j = \frac{D(Z^i_j, Z^-_{j})}{D(Z^i_j, Z^+_{j}) + D(Z^i_j, Z^-_{j})} \quad (40)$$

According to the index of relative closeness $R^i_j$, every hotel $A_i$ will obtain its ranking on every website $P_j$. Thus, we construct the ranking matrix of ratings as:

$$F = \begin{bmatrix} 1 & 2 & \ldots & m \\ A_1 & F_{11} & F_{12} & \cdots & F_{1m} \\ A_2 & F_{21} & F_{22} & \cdots & F_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & F_{m1} & F_{m2} & \cdots & F_{mm} \end{bmatrix} \quad (41)$$

If there are $\pi$ hotels are tied on one website, the ranking result should be separated into $\pi!$ equalized rankings and each of these equalized rankings is weighted $\frac{1}{\pi!}$. We denote $F'_{ig}$ as the set of websites where $A_i$ obtains rank $g$ after separation, the weighted averaging ranking matrix based on rating information $\Pi$ is then calculated as follows:

$$F' = \begin{bmatrix} 1 & 2 & \ldots & m \\ A_1 & \Pi_{11} & \Pi_{12} & \cdots & \Pi_{1m} \\ A_2 & \Pi_{21} & \Pi_{22} & \cdots & \Pi_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & \Pi_{m1} & \Pi_{m2} & \cdots & \Pi_{mm} \end{bmatrix} \quad (42)$$

where $\Pi_{ig}$ is calculated by the following formula:

$$\Pi_{ig} = \sum_{P_j \in F'_{ig}} \frac{N_j}{\pi_j! \sum_h N_h} \quad (43)$$

The number of total reviews on $P_j$ is $N_j$, $\pi_j$ records the number of hotels that are tied on $P_j$ in $F$. Ultimately, by combining $F'$ with the weighted averaging ranking matrix based on only the comments $\Pi$ acquired by the Eq. (32), the extended weighted averaging ranking matrix $M$ is obtained as:

$$M = \xi_r \Pi + \xi_c \Pi \quad (44)$$

where the parameters $\xi_r$ and $\xi_c$ present the importance of average rating information and textual comment information. They satisfy the condition that $\xi_r, \xi_c \geq 0, \xi_r + \xi_c = 1$.

Finally, according to the weighted averaging ranking matrix $M$, we can establish and solve the linear assignment model (45) to determine the ranking of hotels.

$$\max \sum_{i=1}^{m} \sum_{g=1}^{m} M_{ig} \cdot x_{ig} \quad (45)$$

$$\text{s.t.} \begin{cases} \sum_{g=1}^{m} x_{ig} = 1, & i = 1, 2, \ldots, m, \\ \sum_{i=1}^{m} x_{ig} = 1, & g = 1, 2, \ldots, m, \\ x_{ig} = 0 \text{ or } 1, & \forall i, g. \end{cases}$$
The extended methodology can provide customers assistance when details of rating information is incomplete in a great extent or completely unknown. However, if the decision maker can get enough amount of rating details, the original methodology proposed before would be preferred.

5 An illustrative example and comparison analysis

London is famous for its historical legacies and material cultural heritages. It is one of the world’s most visited cities and the top city destination in Europe. According to the reports from the government, more than 31 million travellers spared their overnight visits in London in 2016, while historic landmarks and parks both featured as the leading draws for tourism. Among all fascinating royal parks in London city, the Hyde Park with its central location and various landscapes stands as a best choice for both domestic citizens and international tourists. Suppose that a traveller is about to settle her accommodation near the London Hyde Park, she is concerned about the transportation of Paddington Station. After a brief browse, four hotels that may capture her fancy are selected: “Roseate House London (Roseate)”, “Mercure London Hyde Park (Mercure)”, “Hilton London Hyde Park (Hilton)”, and “Mandarin Oriental Hyde Park (Mandarin)”. All four hotels have similar overall rating scores, so that a further evaluation is supposed to be conducted. The Hyde Park, Pattington Station and all four hotels are marked on the map of London in the following Fig. 7. Roseate and Mercure are close to Pattington while Hilton and Mandarin are close to Hyde Park. Specifically, Mandarin is located at the other end of the park but has an advantage of easy access to museums at south. For convenience, let us denote the set of hotels as:

\[ A = \{A_1 = \text{Roseate}, \ A_2 = \text{Mercure}, \ A_3 = \text{Hilton}, \ A_4 = \text{Mandarin}\} \]

The traveller uses three travel agents for information collection, which are:

\[ P = \{P_1 = \text{TripAdvisor}, \ P_2 = \text{Booking.com}, \ P_3 = \text{Travelocity}\} \]

Since the tourism industry has been severely affected worldwide during the COVID-19 pandemic (Fotiadis et al., 2021; Fang et al., 2021) and multiple tourism strategies were
Table 2  The number of sentences separated from comments of four hotels on three websites

| Hotel $A_i$ | Website $P_j$       | TripAdvisor ($P_1$) | Booking.com ($P_2$) | Travelocity ($P_3$) | Total number |
|-------------|---------------------|---------------------|---------------------|---------------------|--------------|
| Roseate ($A_1$) | 987                 | 443                 | 94                  | 1524                |
| Mercure ($A_2$) | 439                 | 764                 | 164                 | 1367                |
| Hilton ($A_3$) | 276                 | 408                 | 69                  | 753                 |
| Mandarin ($A_4$) | 653                 | 97                  | 39                  | 789                 |
| Total number | 2355                | 1712                | 366                 | 4433                |

evoked by different countries (Collins-Kreiner & Ram, 2020), reviews provided by recent travelers could be more effective for hotel evaluation. By utilizing crawler software, online reviews commented during the period of January 1$^{st}$, 2020 to July 10$^{th}$, 2021 are obtained. Unfortunately, all three websites lack the details of rating scores. To improve the quality of sentiment analysis, the raw data is then filtered according to the following basic rules. (1) The review whose overall rating is obviously different to its comment semantics will be manually dropped as an unqualified evaluation; (2) The review whose comment is unrelated to the hotel evaluation will be manually dropped as an unqualified evaluation; (3) The comment that contains less than two non-repetitive content words will be manually dropped as an unqualified comment. The number of sentences separated from remaining comments of four hotels on three websites is shown in Table 2. From Table 2, we can comprehend that the number of online reviews are unbalanced among websites, and an cross-platform searching can provide customers more comprehensive information.

5.1 Hotel evaluation based on the proposed method

Since the rating details are unavailable, we are compelled to first consider the model discussed in Sects. 4.1–4.5 without using the rating results. The extended model discussed in Sect. 4.6 will be presented in Sect. 5.2.

The model of hotel evaluation is started with data preprocessing. In this paper, we utilize NVivo to capture themes of comments. Initially, we add words “london, paddington, station, hyde, park, roseate, mercure, hilton, mandarin, hotel, tripadvisor, booking, travelocity” into the list of stop words to ensure that they will not bother the frequency analysis. As shown in Fig. 8, NVivo generates the word cloud of possible themes inside the comments. The decision criteria are chosen to be:

$$C = \{c_1 = \text{Room}, \ c_2 = \text{Location}, \ c_3 = \text{Staff}, \ c_4 = \text{Breakfast}\}$$

where $c_1, c_2, c_3$ are concerned by all three websites and $c_4$ is concerned by $P_1$ and $P_2$.

According to the discussion in Sect. 4, we utilize a natural-language processing package “TextBlob” in Python to calculate the emotional tendencies of comment sentences. Then, the overall emotional tendency of evaluations are calculated according to the Eq. (9). The parameter $d$ is chosen to be 0.1, which is less than 0.125, i.e., a half of the standard interval length between two adjacent linguistic terms. The results are presented in the following Table 3.

It is obvious that each website has its own characteristics. Therefore, we utilize the Eqs. (10)–(16) to obtain the semantics division by adjusting the basic division for each web-
Fig. 8 Word cloud of comments on three websites

Table 3 The overall emotional tendencies of evaluations on different websites

| Hotel | Website | Criterion $c_k$ | Room ($c_1$) | Location ($c_2$) | Staff ($c_3$) | Breakfast ($c_4$) |
|-------|---------|-----------------|--------------|-----------------|--------------|------------------|
| $A_1$ | $P_1$   | 0.3527          | 0.3418       | 0.4152          | 0.4577       |
|       | $P_2$   | 0.3473          | 0.5261       | 0.4528          | 0.3455       |
|       | $P_3$   | 0.2236          | 0.6232       | 0.4439          |              |
| $A_2$ | $P_1$   | 0.2302          | 0.2859       | 0.3996          | 0.3427       |
|       | $P_2$   | 0.0622          | 0.4773       | 0.3772          | 0.2797       |
|       | $P_3$   | 0.1364          | 0.4481       | 0.3908          |              |
| $A_3$ | $P_1$   | 0.1233          | 0.4491       | 0.4023          | 0.2755       |
|       | $P_2$   | 0.1065          | 0.5410       | 0.3893          | 0.2417       |
|       | $P_3$   | 0.0679          | 0.4646       | 0.4963          |              |
| $A_4$ | $P_1$   | 0.2416          | 0.2728       | 0.3458          | 0.3994       |
|       | $P_2$   | 0.0946          | 0.6429       | 0.3216          | 0.1220       |
|       | $P_3$   | 0.1691          | 0.4661       | 0.4054          |              |

The site. The parameter $t$ is set to be $t = \tau = 4$. Then, according to the Eqs. (17) and (18), we construct the evaluation PLTS $L_{j,k}^i$ by PLTS theory. The decision matrix $D_{j,k}^i = [L_{j,k}^i]_{m \times \Delta_j}$ is constructed in Table 4.

Based on the results of Table 4, we can then calculate the fuzzy measures of criteria on each website by utilizing the Eq. (28). The results are: $w_1 = [0.4663, 0.3538, 0.4938, 0.1947]$, $w_2 = [0.4056, 0.2036, 0.5084, 0.3317]$, and $w_3 = [0.4762, 0.2219, 0.4290]$. According to the Eq. (24), we further calculate the parameter $\lambda_j$ as: $\lambda_1 = -0.7339, \lambda_2 = -0.6903$ and $\lambda_3 = -0.3256$ respectively. By using Definition 4 and the Eq. (27), we can rank the PLTSs of evaluations about each hotel on each website. The parameters are chosen to be $\alpha = 1.5$ and $a = \sqrt{9}$. Then, we calculate the fuzzy measures for combinations of criteria based on these ranking series. Ultimately, by utilizing the Eq. (30), we can obtain the hotel $A_i$’s overall evaluation on the website $P_j$. The aggregated results denoted as $L_j^i$ and the value of score function denoted as $E(L_j^i)$ are presented in Table 5. Thus, the ranking result is coincidentally $A_1 > A_4 > A_3 > A_2$ on all three websites. The weighted averaging ranking matrix $\Pi$ is directly obtained as follows:
Table 4 The decision matrix $D_{j,k}^i = [L_{j,k}^i]_{m \times \Delta_j}$

| Hotel | Website | Criterion | $s_{-4}$ | $s_{-3}$ | $s_{-2}$ | $s_{-1}$ | $s_0$ | $s_1$ | $s_2$ | $s_3$ | $s_4$ |
|-------|---------|-----------|----------|----------|----------|----------|--------|--------|--------|--------|--------|
| $A_1$ | $P_1$   | $c_1$     | 0.0000   | 0.0025   | 0.0124   | 0.0534   | 0.2055 | 0.2620 | 0.3133 | 0.1245 | 0.0264 |
|       |         | $c_2$     | 0.0000   | 0.0000   | 0.0000   | 0.0128   | 0.1879 | 0.2684 | 0.2580 | 0.1743 | 0.0986 |
|       |         | $c_3$     | 0.0000   | 0.0000   | 0.0000   | 0.0250   | 0.1470 | 0.2540 | 0.3485 | 0.1417 | 0.0838 |
|       |         | $c_4$     | 0.0000   | 0.0002   | 0.0062   | 0.0408   | 0.1708 | 0.2091 | 0.2614 | 0.1654 | 0.1460 |
|       | $P_2$   | $c_1$     | 0.0014   | 0.0166   | 0.0478   | 0.0713   | 0.2115 | 0.1850 | 0.2771 | 0.1563 | 0.0330 |
|       |         | $c_2$     | 0.0000   | 0.0000   | 0.0034   | 0.0379   | 0.1772 | 0.1624 | 0.2343 | 0.2232 | 0.1616 |
|       |         | $c_3$     | 0.0000   | 0.0001   | 0.0094   | 0.0532   | 0.1078 | 0.2368 | 0.3405 | 0.1806 | 0.0717 |
|       |         | $c_4$     | 0.0000   | 0.0060   | 0.0667   | 0.1070   | 0.1994 | 0.1340 | 0.1761 | 0.2052 | 0.1056 |
|       | $P_3$   | $c_1$     | 0.0227   | 0.0000   | 0.0076   | 0.0618   | 0.2731 | 0.2495 | 0.2523 | 0.1241 | 0.0089 |
|       |         | $c_2$     | 0.0000   | 0.0000   | 0.0000   | 0.0204   | 0.1160 | 0.1466 | 0.2819 | 0.3585 | 0.0766 |
|       |         | $c_3$     | 0.0000   | 0.0000   | 0.0070   | 0.0297   | 0.1697 | 0.2249 | 0.2504 | 0.1872 | 0.1312 |
| Hotel | Website | Criterion | $s_{-4}$ | $s_{-3}$ | $s_{-2}$ | $s_{-1}$ | $s_0$ | $s_1$ | $s_2$ | $s_3$ | $s_4$ |
|-------|--------|-----------|---------|---------|---------|---------|-------|-------|-------|-------|-------|
| $A_2$ | $P_1$  | $c_1$     | 0.0047  | 0.0032  | 0.0206  | 0.1043  | 0.2874 | 0.3113 | 0.1847 | 0.0646 | 0.0192 |
|       |        | $c_2$     | 0.0000  | 0.0000  | 0.0078  | 0.0143  | 0.1872 | 0.3299 | 0.2423 | 0.1142 | 0.1042 |
|       |        | $c_3$     | 0.0058  | 0.0000  | 0.0032  | 0.0207  | 0.1855 | 0.2365 | 0.3461 | 0.1514 | 0.0508 |
|       |        | $c_4$     | 0.0000  | 0.0000  | 0.0061  | 0.0490  | 0.2615 | 0.1780 | 0.2349 | 0.1539 | 0.1167 |
| $P_2$ |        | $c_1$     | 0.0000  | 0.0011  | 0.0262  | 0.1830  | 0.3325 | 0.2256 | 0.1647 | 0.0556 | 0.0113 |
|       |        | $c_2$     | 0.0000  | 0.0000  | 0.0100  | 0.0908  | 0.1657 | 0.1717 | 0.2843 | 0.2367 | 0.0409 |
|       |        | $c_3$     | 0.0005  | 0.0083  | 0.0198  | 0.0979  | 0.1595 | 0.2058 | 0.3282 | 0.1328 | 0.0471 |
|       |        | $c_4$     | 0.0000  | 0.0039  | 0.0126  | 0.0894  | 0.2762 | 0.1810 | 0.2505 | 0.1579 | 0.0285 |
| $P_3$ |        | $c_1$     | 0.0000  | 0.0000  | 0.0090  | 0.1452  | 0.3340 | 0.2979 | 0.1611 | 0.0311 | 0.0217 |
|       |        | $c_2$     | 0.0000  | 0.0000  | 0.0000  | 0.0408  | 0.1588 | 0.2498 | 0.2411 | 0.2119 | 0.0977 |
|       |        | $c_3$     | 0.0000  | 0.0000  | 0.0092  | 0.0510  | 0.1138 | 0.3156 | 0.2988 | 0.1499 | 0.0617 |
| $A_3$ | $P_1$  | $c_1$     | 0.0093  | 0.0171  | 0.0168  | 0.1037  | 0.3718 | 0.2356 | 0.1612 | 0.0703 | 0.0142 |
|       |        | $c_2$     | 0.0000  | 0.0026  | 0.0198  | 0.0401  | 0.1751 | 0.2281 | 0.2047 | 0.2099 | 0.1196 |
|       |        | $c_3$     | 0.0000  | 0.0000  | 0.0124  | 0.0430  | 0.1935 | 0.2213 | 0.2725 | 0.1694 | 0.0878 |
|       |        | $c_4$     | 0.0000  | 0.0215  | 0.0264  | 0.0512  | 0.3132 | 0.1644 | 0.1559 | 0.2048 | 0.0626 |
| $P_2$ |        | $c_1$     | 0.0145  | 0.0118  | 0.0272  | 0.1770  | 0.3205 | 0.1756 | 0.1970 | 0.0619 | 0.0145 |
|       |        | $c_2$     | 0.0000  | 0.0000  | 0.0075  | 0.0531  | 0.1525 | 0.1180 | 0.2768 | 0.2460 | 0.1461 |
|       |        | $c_3$     | 0.0000  | 0.0040  | 0.0337  | 0.0574  | 0.2005 | 0.1875 | 0.3548 | 0.1448 | 0.0209 |
|       |        | $c_4$     | 0.0000  | 0.0250  | 0.0255  | 0.1631  | 0.2171 | 0.1251 | 0.1545 | 0.1537 | 0.1360 |
| $P_3$ |        | $c_1$     | 0.0023  | 0.0235  | 0.0324  | 0.1105  | 0.3987 | 0.2449 | 0.1442 | 0.0407 | 0.0027 |
|       |        | $c_2$     | 0.0000  | 0.0000  | 0.0032  | 0.0118  | 0.1859 | 0.1939 | 0.2757 | 0.2410 | 0.0886 |
|       |        | $c_3$     | 0.0000  | 0.0054  | 0.0337  | 0.0455  | 0.1628 | 0.1907 | 0.2366 | 0.2134 | 0.1120 |
| Hotel | Website | Criterion | $s_{-4}$ | $s_{-3}$ | $s_{-2}$ | $s_{-1}$ | $s_{0}$ | $s_{1}$ | $s_{2}$ | $s_{3}$ | $s_{4}$ |
|-------|--------|-----------|---------|---------|---------|---------|--------|--------|--------|--------|--------|
| $A_4$ | $P_1$  | $c_1$     | 0.0000  | 0.0001  | 0.0074  | 0.0659  | 0.2930  | 0.2543  | 0.2233  | 0.0918  | 0.0641  |
|      |        | $c_2$     | 0.0000  | 0.0000  | 0.0092  | 0.0246  | 0.2883  | 0.2163  | 0.2276  | 0.1600  | 0.0740  |
|      |        | $c_3$     | 0.0000  | 0.0000  | 0.0032  | 0.0144  | 0.2271  | 0.2576  | 0.2783  | 0.1468  | 0.0726  |
|      |        | $c_4$     | 0.0000  | 0.0000  | 0.0000  | 0.0328  | 0.2472  | 0.1683  | 0.2516  | 0.1952  | 0.1050  |
| $P_2$ |        | $c_1$     | 0.0000  | 0.0000  | 0.0044  | 0.1161  | 0.3462  | 0.2611  | 0.1296  | 0.0926  | 0.0501  |
|      |        | $c_2$     | 0.0000  | 0.0000  | 0.0000  | 0.0892  | 0.1615  | 0.1152  | 0.1587  | 0.2907  | 0.1848  |
|      |        | $c_3$     | 0.0000  | 0.0000  | 0.0057  | 0.0864  | 0.1732  | 0.2983  | 0.2060  | 0.1603  | 0.0700  |
|      |        | $c_4$     | 0.0000  | 0.0000  | 0.0000  | 0.0271  | 0.2747  | 0.3599  | 0.2066  | 0.1081  | 0.0236  |
| $P_3$ |        | $c_1$     | 0.0000  | 0.0125  | 0.0349  | 0.1112  | 0.3192  | 0.1505  | 0.2277  | 0.1043  | 0.0398  |
|      |        | $c_2$     | 0.0000  | 0.0000  | 0.0092  | 0.1267  | 0.1768  | 0.1832  | 0.1244  | 0.2304  | 0.1493  |
|      |        | $c_3$     | 0.0000  | 0.0000  | 0.0204  | 0.0495  | 0.1806  | 0.2136  | 0.2889  | 0.1458  | 0.1011  |
\[
\Pi = \begin{bmatrix}
1^\text{st} & 2^\text{nd} & 3^\text{rd} & 4^\text{th} \\
A_1 & 1 & 0 & 0 & 0 \\
A_2 & 0 & 0 & 0 & 1 \\
A_3 & 0 & 0 & 1 & 0 \\
A_4 & 0 & 1 & 0 & 0 \\
\end{bmatrix}
\]  
(46)

Therefore, the ranking result will be \( A_1 > A_4 > A_3 > A_2 \), which suggests that the Roseate House London hotel is more preferred by consumers.

5.2 Hotel evaluation based on the extended method

The extended model discussed in Sect. 4.6 utilizes overall ratings to obtain a prior ranking result. Specifically, for the four hotels awaiting our evaluation, we first collect average rating information from all three websites to form Tables 6, 7 and 8.

For convenience, we assume that all criteria are equally weighted, i.e., the customer has an indifferent prior upon criteria. By utilizing the TOPSIS method, we then obtain the ranking results:

\[
A_4 > (A_1 \sim A_2) > A_3 \quad \text{on} \quad P_1; \quad A_4 > A_1 > A_3 > A_2 \quad \text{on} \quad P_2; \quad A_1 > A_4 > A_2 > A_3 \quad \text{on} \quad P_3.
\]

Thus, we further construct the ranking matrix based on rating information \( F \) as:

\[
F = \begin{bmatrix}
1^\text{st} & 2^\text{nd} & 3^\text{rd} & 4^\text{th} \\
A_1 & 1 & 2 & 0 & 0 \\
A_2 & 0 & 1 & 1 & 1 \\
A_3 & 0 & 0 & 1 & 2 \\
A_4 & 2 & 1 & 0 & 0 \\
\end{bmatrix}
\]  
(47)

\( A_1 \) and \( A_2 \) are tied on \( P_1 \). In this case, we separate the ranking into \( A_4 > A_1 > A_2 > A_3 \) and \( A_4 > A_2 > A_1 > A_3 \). Both of them are weighted \( \frac{1}{2} \). Therefore, the weighted averaging ranking matrix based on rating information \( \Pi \) will be:

\[
\Pi = \begin{bmatrix}
1^\text{st} & 2^\text{nd} & 3^\text{rd} & 4^\text{th} \\
A_1 & 0.5756 & 0.2122 & 0.2122 & 0.0000 \\
A_2 & 0.0000 & 0.2122 & 0.4112 & 0.3765 \\
A_3 & 0.0000 & 0.0000 & 0.3765 & 0.6235 \\
A_4 & 0.4244 & 0.5756 & 0.0000 & 0.0000 \\
\end{bmatrix}
\]  
(48)

Given \( \xi_r = 0.75, \xi_c = 0.25 \), i.e., the customer concerns more about rating criteria than comment criteria, the extended weighted averaging ranking matrix \( M \) is obtained:

\[
M = 0.75\Pi + 0.25\Pi = \begin{bmatrix}
1^\text{st} & 2^\text{nd} & 3^\text{rd} & 4^\text{th} \\
A_1 & 0.6817 & 0.1592 & 0.1592 & 0.0000 \\
A_2 & 0.0000 & 0.1592 & 0.3084 & 0.5324 \\
A_3 & 0.0000 & 0.0000 & 0.5324 & 0.4676 \\
A_4 & 0.3183 & 0.6817 & 0.0000 & 0.0000 \\
\end{bmatrix}
\]  
(49)

By establishing and solving the linear assignment model (45), the result is still \( A_1 > A_4 > A_3 > A_2 \).
Table 5  The aggregated evaluations $L_{ij}$ and the values of their score functions $E(L_{ij})$

| Website | Hotel | $s_{-4}$ | $s_{-3}$ | $s_{-2}$ | $s_{-1}$ | $s_0$ | $s_1$ | $s_2$ | $s_3$ | $s_4$ | $E(L_{ij})$ |
|---------|-------|---------|---------|---------|---------|------|------|------|------|------|---------|
| $P_1$   | $A_1$ | 0.0000  | 0.0005  | 0.0036  | 0.0297  | 0.1751| 0.2511| 0.2974| 0.1530| 0.0896| 0.5618  |
|         | $A_2$ | 0.0027  | 0.0006  | 0.0084  | 0.0400  | 0.2201| 0.2676| 0.2625| 0.1242| 0.0739| 0.4781  |
|         | $A_3$ | 0.0018  | 0.0061  | 0.0172  | 0.0542  | 0.2316| 0.2212| 0.2168| 0.1683| 0.0829| 0.4878  |
|         | $A_4$ | 0.0000  | 0.0000  | 0.0045  | 0.0297  | 0.2553| 0.2316| 0.2529| 0.1484| 0.0776| 0.5035  |
| $P_2$   | $A_1$ | 0.0002  | 0.0041  | 0.0255  | 0.0632  | 0.1570| 0.1936| 0.2774| 0.1896| 0.0895| 0.5507  |
|         | $A_2$ | 0.0002  | 0.0045  | 0.0176  | 0.1097  | 0.2125| 0.1977| 0.2764| 0.1451| 0.0361| 0.4090  |
|         | $A_3$ | 0.0025  | 0.0093  | 0.0249  | 0.1075  | 0.2164| 0.1535| 0.2543| 0.1535| 0.0781| 0.4494  |
|         | $A_4$ | 0.0000  | 0.0000  | 0.0033  | 0.0812  | 0.2197| 0.2660| 0.1832| 0.1654| 0.0813| 0.4838  |
| $P_3$   | $A_1$ | 0.0086  | 0.0000  | 0.0057  | 0.0398  | 0.1971| 0.2169| 0.2581| 0.2012| 0.0726| 0.5345  |
|         | $A_2$ | 0.0000  | 0.0000  | 0.0071  | 0.0845  | 0.2075| 0.2942| 0.2336| 0.1185| 0.0545| 0.4258  |
|         | $A_3$ | 0.0009  | 0.0111  | 0.0264  | 0.0627  | 0.2576| 0.2120| 0.2102| 0.1539| 0.0653| 0.4266  |
|         | $A_4$ | 0.0000  | 0.0047  | 0.0234  | 0.0901  | 0.2324| 0.1829| 0.2292| 0.1488| 0.0885| 0.4670  |
| Table 6 | The average rating scores of hotels on TripAdvisor ($P_1$) |
|---------|--------------------------------------------------|
|         | Roseate ($A_1$) | Mercure ($A_2$) | Hilton ($A_3$) | Mandarin ($A_4$) |
| Overall ($\tau_{1,1}$) | 4.5 | 4.5 | 4.0 | 5.0 |
| Location ($\tau_{1,2}$) | 4.5 | 4.5 | 4.5 | 5.0 |
| Cleanliness ($\tau_{1,3}$) | 4.5 | 4.5 | 4.5 | 5.0 |
| Service ($\tau_{1,4}$) | 4.5 | 4.5 | 4.5 | 5.0 |
| Value ($\tau_{1,5}$) | 4.0 | 4.0 | 4.0 | 4.5 |
| Number of Ratings | 2150 | 827 | 855 | 211 |

| Table 7 | The average rating scores of hotels on Booking.com ($P_2$) |
|---------|--------------------------------------------------|
|         | Roseate ($A_1$) | Mercure ($A_2$) | Hilton ($A_3$) | Mandarin ($A_4$) |
| Overall ($\tau_{2,1}$) | 8.8 | 7.9 | 8.1 | 9.2 |
| Staff ($\tau_{2,2}$) | 9.3 | 8.6 | 8.8 | 9.4 |
| Value for Money ($\tau_{2,3}$) | 8.2 | 7.4 | 7.4 | 8.1 |
| Facilities ($\tau_{2,4}$) | 8.6 | 7.8 | 7.7 | 9.3 |
| Location ($\tau_{2,5}$) | 9.4 | 8.9 | 9.0 | 9.6 |
| Cleanliness ($\tau_{2,6}$) | 9.1 | 8.4 | 8.4 | 9.4 |
| Comfort ($\tau_{2,7}$) | 9.1 | 8.2 | 8.2 | 9.5 |
| Number of ratings | 733 | 1703 | 987 | 164 |

| Table 8 | The average rating scores of hotels on Travelocity ($P_3$) |
|---------|--------------------------------------------------|
|         | Roseate ($A_1$) | Mercure ($A_2$) | Hilton ($A_3$) | Mandarin ($A_4$) |
| Overall ($\tau_{3,1}$) | 4.4 | 4.2 | 4.1 | 4.3 |
| Cleanliness ($\tau_{3,2}$) | 4.6 | 4.5 | 4.4 | 4.5 |
| Service and staff ($\tau_{3,3}$) | 4.6 | 4.4 | 4.4 | 4.6 |
| Amenities ($\tau_{3,4}$) | 4.5 | 4.3 | 3.7 | 4.4 |
| Property condition ($\tau_{3,5}$) | 4.3 | 4.3 | 4.0 | 4.1 |
| Number of ratings | 989 | 357 | 406 | 144 |

### 5.3 Comparison with Choquet integral based on traditional PLTS operators

This section would give an example for comprehending the advantages of probabilistic linguistic DAWA operator (Definition 3) in Choquet integral operation compared to the traditional PLTS operators.

According to Lin and Xu (2018) and the result from Wang et al. (2014), the weighted averaging operator of two PLTSs is defined by the following Eq. (50):

$$
\mu_1 L_1(p) \oplus \mu_2 L_2(p) = \bigcup_{L_1^{(k_1)} \in L_1(p_1)} \left\{ f^{-1} \left( \mu_1 f(L_1^{(k_1)}) + \mu_2 f(L_2^{(k_2)}) \right) \left( p_1^{(k_1)} p_2^{(k_2)} \right) \right\}
$$

(50)
Annals of Operations Research

Fig. 9  The number of PLEs with nonzero possibilities of being used in $L^i_j$

Table 9  The value of score function $E(L^i_j)$

| Hotel | Website    | Number of PLEs |
|-------|------------|---------------|
|       | TripAdvisor | 2,304          | 4,032          |
|       | Booking.com | 336           |
|       | Travelocity |               |
|       | Mercure     | 3,528          | 4,032          |
|       | TripAdvisor | 294           |
|       | Booking.com |               |
|       | Travelocity |               |
|       | Hilton      | 4,032          | 4,032          |
|       | TripAdvisor | 504           |
|       | Booking.com |               |
|       | Travelocity |               |
|       | Mandarin    | 2,352          |
|       | TripAdvisor | 1,764         |
|       | Booking.com |               |
|       | Travelocity | 392           |

Accordingly, the probabilistic linguistic Choquet integral is modified as follows:

$$\int \mathcal{L} d\mu = \bigoplus_{i=1}^{n} \left[ \mu(X(i)) - \mu(X(i+1)) \right] \mathcal{L}(x(i))$$

The drawback of the probabilistic linguistic Choquet integral based on traditional PLTS operators is lurking under the traversal operation itself. On one hand, each probabilistic linguistic element (PLE) in one set will be used for calculation of the Eq. (50) with all PLEs in other sets. Therefore, with the increase of number of decision criteria, the result of Choquet integral will have an exponential increase upon the number of PLEs. Most of these PLEs will have similar linguistic terms while their possibilities of being used will be extremely small approaching 0. On the other hand, the reverse of linguistic scale function $f$ is not concise to obtain. The calculation will aggravate the burden upon both space complexity and time complexity.

As recorded in Fig. 9, replacing Choquet integral Eq. (30) with the Eq. (51) in our proposed method leads to a result of large PLTSs. It is noteworthy that although the website of TripAdvisor ($P_1$) and Booking.com ($P_2$) uses just one more criterion than the website of Travelocity ($P_3$), the result of aggregated evaluation $L^1_j$ and $L^2_j$ has far more PLEs than the result of $L^3_j$. However, as shown in Table 9, the ranking result is kept to be $A_1 > A_4 > A_3 > A_2$. Therefore, the DAWA operator is more competent for the current scenario.
5.4 Comparison with other hotel evaluation methodologies related to fuzzy set theory

The current hotel evaluation methodologies can be categorized according to multiple rules. With regard to the source of information, decision models can be divided as utilizing data from one fixed website and utilizing data from multiple websites. With regard to the type of information, most methods only focus on a unique kind of information, whether numerical ratings or textual comments, while the combination of information is also available for discussion. From the perspective of characterizing customers’ psychological behaviors, the existing methods can then be divided by whether consider the unbalanced effect of human cognitive upon different level of evaluations. Table 10 summarises some typical hotel evaluation methodologies related to fuzzy set theory and our proposed method with their characteristics.

In Table 10, with regard to the source of information, our method considers collecting online evaluations from multiple websites and further discusses the analysis upon websites’ inherent differences. The method extends the current research and starts up an attempt of characterizing customers’ cross-platform searching behaviors for hotel selection. During the decision making process, customers may encounter situations that one website lacks the information of some certain hotels, or one hotel enjoys distanced reputations on different websites. Our cross-platform searching model can effectively bring customers more valuable information.

Regarding the type of information, traditional methods focus on only the ratings or the comments, which could loss a part of information. On the other hand, rating scores are too definite and limited to express the comprehensive meaning of evaluations (Li et al., 2013). Therefore, taking both sides into consideration could not only enlarge the quantity of data collection, but also improve the ability of analyzing customers’ intentions behind their evaluations.

Customers’ subjectivity is discussed by Zhang et al. (2020), Nie et al. (2020), Zhao et al. (2021) and this paper, but with differentiated ideas. Zhang et al. (2020) utilized linguistic scale function to characterize the unbalanced effect of linguistic terms, which was identical with our initial intention. The divergence emerges when they choose the utility theory to construct the linguistic scale function, while we choose the Weber-Fechner Law as our theoretical foundation to line out the function. It is quite hard to say that whether the utility theory is superior to the Weber-Fechner Law or not. The choice is just originated from the viewpoint of understanding customers’ evaluating behaviors. The work of Nie et al. (2020) introduced the evidence theory to ensure the rational decisions. Their investigation can play an important role for our data preprocessing, finding out those reviews of irrational style, which will definitely optimize the structure of our existing model. Zhao et al. (2021) introduced the linguistic scale function by adding a parameter to enhance the impact of negative evaluations. Another core concept for understanding customers’ evaluating behaviors is the prospect theory (Kahneman & Tversky, 1979), which was also discussed by Zhang et al. (2020). The reason why we prefer the Weber-Fechner Law instead of it is the consideration that customers may fail to establish their reference points when rating and commenting. It is quite hard to say that customers would like to share a common benchmark when evaluating their experiences of accommodation.

The work of Zhao et al. (2021) also considered the multi-source information fusion for hotel evaluation, which is similar to ours. However, their approach considered the ratings and comments separately, and the diversity of websites were only considered when aggregating rating information. When rating criteria considered by the different websites do not coincide,
| Article               | Method   | Source of information | Type of information | Customers’ subjectivity | Processing information diversity | Criteria’s Interactions |
|----------------------|----------|-----------------------|---------------------|-------------------------|----------------------------------|-------------------------|
| Yu et al. (2018)     | LDA\(^a\) | Single                | Ratings             | Not considered          | Not considered                   | Not considered          |
| Kwok and Lau (2019)  | IFS\(^b\) | Single                | Ratings             | Not considered          | Not considered                   | Not considered          |
| Zhang et al. (2020)  | LDA\(^a\) | Single                | Comments            | Linguistic scale function and utility theory | Not considered                   | Not considered          |
| Nie et al. (2020)    | LDA\(^a\) | Single                | Comments            | Evidence theory         | Not considered                   | Not considered          |
| Zhao et al. (2021)   | PLTS\(^c\) | Multiple             | Ratings and comments | Linguistic scale function and risk attitude | Generating artificial rating PLTSs for missing criteria | Not considered          |
| This paper           | PLTS\(^c\) | Multiple             | Ratings and comments | Linguistic scale function and Weber-Fechner Law | Defining semantics division to form rating and comment PLTSs | Fuzzy measure and Choquet integral |

\(^a\) Linguistic distribution assessment  
\(^b\) Intuitionistic fuzzy set  
\(^c\) Probabilistic linguistic term set
Zhao et al. (2021) proposed a method of generating artificial rating PLTSs for missing criteria by considering the correlation between the missing criteria and the coincided criteria. Thus, the number of criteria shared by different websites will influence the robustness of the model. Moreover, inspired by the work of Li et al. (2013) and Wu et al. (2014), we further consider the situation that decision criteria are interrelated and introduce the $\lambda$-fuzzy-measure-based probabilistic linguistic Choquet integral. To identify the interrelation among criteria, we mainly investigate a pair of probabilistic linguistic entropy and cross-entropy. Considering the increasing complexity and fuzzy uncertainty of information, our proposed method provides an idea of aiding customers’ decision making under more complicated circumstances.

6 Conclusions

The work of this paper elaborates a framework of cross-platform hotel evaluation, which expands the scope of information collection and integration across different accommodation websites. To facilitate the operations of PLTS, this paper designs a revised definition of PLTS. Taking the inherent differences among different websites into consideration, this paper investigates that the information is supposed to be initially integrated inside each website respectively, and adapts the weighted averaging linear assignment model to rank hotels across the board. During the information integration process, this paper also considers the situation that the decision criteria are interrelated, and then proposes the probabilistic linguistic Choquet integral based on the probabilistic linguistic DAWA operator and fuzzy measure theory. For the convenience of application, this paper further defines a pair of probabilistic linguistic entropy and cross-entropy for the criteria information. This paper also makes an attempt of simulating the psychological behaviors of customers in real decision making and online review scenarios. On one hand, this paper makes an attempt of developing a method that enables adjusting linguistic-term formations among different websites to make full use of information. On the other hand, by adapting the Weber-Fechner Law with the linguistic scale function, this paper develops a novel unbalanced linguistic scale function. In general, our proposed method can provide supports for the customers, as well as helping hotel managers to improve the quality of service by analyzing customers’ general concerns and experiences.

At the same time, we shall also notice that the research of this paper is conducted with several limitations. On one hand, information about the hotel: the geometric information such as hotel’s surroundings (Ghose et al., 2012); the visualized information such as rooms’ pictures and hotel’s style of design (Noone & Robson, 2016); the responses of managers with regard to customers’ reviews (Chevalier et al., 2018), is not considered in our discussion. On the other hand, information about the travelling customer: her purpose of travel (Noone & Robson, 2016; Wang et al., 2020); the heterogeneity of customers (Ebbes et al., 2013), their social networks (Ma et al., 2015), is also informative and can provide us directions about improving the model of hotel evaluation. We are looking forward to future extensions of hotel evaluation method based on integrating information from multiple websites.

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