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Evaluating Economy Hotel Website Service Quality: A Hybrid Bounded Rationality Behavioral Decision Support Model

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Abstract: Hotel website service quality evaluation has gained extensive attention. However, previous studies have given little concern about human hesitance and uncertainty in judgments. Moreover, they do not consider hotel managers and customers' psychological behaviors simultaneously. This study explores criteria for evaluating hotel performance and proposes a hybrid evaluation model for the hesitation and uncertainty in the service quality evaluation of economy hotel websites, and applied to the actual economy hotel websites. The model introduces the probabilistic linguistic term sets to describe customers and managers' qualitative assessments and use analytical network process to prioritize hotel website features. Then, it develops an integrated TODIM-PROMETHEE II method to rank alternatives considering both hotel managers and customers' psychological factors. Furthermore, we illustrate the effectiveness of the hybrid evaluation model through a case of economy hotel websites in China. Service competence and customer relationship are the two most important performance features for economy hotel websites. Finally, conclusions and implications are drawn from the results of case study.

Keywords: hotel website service quality; probabilistic linguistic term set; performance evaluation; ranking methods

MSC: 90B50

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1. Introduction

In the hospitality industry, a hotel website is a low-cost distribution channel to accommodate customers' growing demands for online hotel booking [1]. Due to the low cost of information search and inspection for hotel reservations, customers frequently evaluate and compare products from different hotel websites to gain an optimal deal. In particular, the hotel reservation information quality and some other indicators may remarkably affect customers' booking intentions. Thus, hotel website evaluation is critical for customers to make a satisfactory online purchase decision among various choices [2]. Simultaneously, website evaluation can also help hotel managers interpret the effectiveness of their websites in delivering helpful and smart information and good services to customers. In other words, conducting an in-depth evaluation of hotel websites is considered essential for both customers and hotel managers.

The evaluation of hotel websites generally refers to the evaluation of hotel websites' functionality or service quality [3]. Each type often involves several candidates to be evaluated by a group of customers or experts according to various interacting website features thereby can be recognized as a multi-experts multi-criteria decision-making (MCDM) problem. Given the hesitancy and complexity of human cognition, decision-makers (DMs) prefer to give qualitative assessments of the service performance of hotel websites rather than crisp values [4]. Therefore, it requires the combination between an appropriate linguistic representation tool and a multi-experts MCDM method to complete the hotel websites' service quality evaluation task.

The multi-experts MCDM processes generally involve two main phases: criteria weight determination and alternative ranking generation. As for the first phase, existing MCDM methods often assume that the criteria are independent, which is not always true in real-world problems [5]. In the field of hotel website service quality evaluation, there are complex interrelationships among diverse evaluation dimensions and criteria. For example, it generally involves two components when evaluating the customer relationship of a hotel website: interactivity and virtual involvement. Hotel user interactivity refers to the interaction and communication between the hotel and its customers to improve user experience and satisfaction. This interactivity can be reflected in several aspects, such as the website or application interface when booking a room, the front desk service when checking in, the facilities and services in the rooms, and the service in the restaurants. Virtual involvement of hotel users refers to user engagement activities based on Internet and digital technologies that allow users to experience the hotel and its services through virtual means without physically arriving at the hotel. There contains inner dependence between them. To deal with this issue, a criteria weight determination method that can capture complex interrelationships among criteria is required. ANP (Analytic Network Process) [6] is a useful method that is widely used for the criterion weight determination. Different from the traditional AHP (Analytic Hierarchy Process) [7] method, the ANP allows for interdependency, external dependence and feedback among decision criteria, so it is more suitable for solving the hotel website service quality evaluation problem in this study.

As for the alternative ranking phase, a widely used list of well-documented MCDM methods include the WSM (Weighted Sum Model), MAUT (Multi-Attribute Utility Theory), TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) [8], TODIM (an acronym in Portuguese of interactive and multicriteria decision making) [9], and outranking-based methods, such as ELECTRE (Elimination and Choice Expressing the Reality) [10] and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) methods [11]. These methods can be roughly classified into three types: the outranking methods, utility-based methods and rule-based methods. The outranking methods involve methods such as PROMETHEE, TODIM. The utility-based methods mainly involve the WSM, MAUT, TOPSIS and various aggregation-based methods. And the rule-based methods utilize the relevant knowledge of fuzzy logic to aggregate the criteria in the form of a decision function, which is a mathematical mapping of decision rules. In real applications, each type of method has its advantages and disadvantages. For example, the utility value-based methods hinge upon the additive utility assumption and can only deal with single-dimensional MCDM problems [12]. Single-dimensional MCMD problems are problems that require the use of MCMD tools for transformation and analysis when working with data in a single dimension (e.g., date, time, geographic location, etc.). In addition, most outranking methods suffer from subjectivity and ranking reversals, but they use relative values instead of actual ones and can therefore be used in single- or multi-dimensional decision-making scenarios. The rule-based methods need to design decision-making rules according to different problems, and it is complex to establish a realistic model and solve it. To take the merits of the outranking method and the utility-based method and enhance the rationality of alternative ranking, this paper aims to propose a hybrid MCDM method for hotel website service quality evaluation.

The PROMETHEE II method is a representative and commonly used outranking method, which can generate a complete alternative ranking and is more effective than other outranking methods in certain decision scenarios. For example, it can reduce DMs' subjective randomness than the ELECTRE method and require less computing time than the Qualitative Comparative Analysis Flexible (QUALIFLEX) method when the candidate alternatives are very huge [13]. Therefore, this paper chooses the PROMETHEE II method to tackle the hotel website evaluation problem. In this method, the preference function can measure the preference degree between two arbitrary alternatives, which is usually quantified using distance measures between two alternatives under a certain criterion. Traditional PROMETHEE II and its variants under diverse fuzzy contexts often take into account six types of generalized criteria in the selection of a specific preference function, namely, the usual, U-shaped, V-shaped, level, V-shaped with indifference, and Gaussian criteria [14]. However, all the above criterion types do not consider DMs' psychological behaviors, which may generate a remarkable influence on decision results. Unlike these methods, the TODIM method relies on a value function that provides the dominance degree of each alternative over the others under different criteria [15]. The S-shaped value function which is based on the prospect theory allows the consideration of DMs' bounded rationality which is more cater for real decision scenarios. Benefiting from the advantages of the TODIM method, this study incorporates the TODIM method into the PROMETHEE II to construct a TODIM-based closeness coefficient model between each pair of alternatives to consider DMs' psychological behavior. It is worth noting that this study is different from the previous work [16], although they all use the TODIM-PROMETHEE method to rank the alternatives, but the literature [16] used the probability linguistic Z-number to describe the uncertainty. This study uses probabilistic linguistic term sets (PLTSs), which is mainly determined to be more in line with specific decision-making scenarios and to consider the habits of decision-makers. In addition, for the determination of the criterion weight, this study considers the inter dependence between the criteria using the PLTSs-based ANP method to obtain more reasonable ranking results.

This paper proposes a hybrid hotel website service quality evaluation method by integrating PLTSs and a bounded rationality-based decision support model named probabilistic linguistic ANP-TODIM-PROMETHEE II. Firstly, PLTSs are used to model both hotel managers and customers' qualitative assessments. Then, a probabilistic linguistic ANP module is constructed to determine criteria weights, which consider multiple dimensions and sub-criteria, and interrelationships or feedback among criteria. Lastly, an integrated TODIM-PROMETHEE II method is constructed to determine alternative ranking.

In summary, this study presents the following two main contributions:

(1) To identify, analyze, and prioritize the criteria that significantly affect hotel managers' and customers' satisfaction with hotel website performance, we propose a PLTSs-based ANP approach. In detail, the PLTSs is introduced for the rational interpretation of qualitative evaluations by evaluation teams consisting of hotel managers and customers. To apply the ANP method, an improved PLTSs-based distance measure is proposed. The ANP method based on PLTSs can capture the interrelationship and feedback among various criteria, and is suitable for determining the criterion weights of different MCDM problems.

(2) Human psychology and risk attitude will affect the evaluation and judgment of things. Considering the psychological factors of evaluators, this study combined the TODIM-PROMETHEE II method to establish a hybrid decision support model with bounded rational behavior. The evaluation results of three Chinese economy hotel websites show the effectiveness of the proposed framework and provide a reference for evaluating and selecting the optimal hotel websites. The proposed framework is easy to operate and implement, provides a new reference for quality evaluation, and can also be applied to other application fields.

The rest of the paper is organized as follows. Section 2 reviews some literature to construct a hierarchical criteria system for hotel website service evaluation. Section 3 presents the research methodology for hotel website evaluation. Section 4 illustrates the applicability of the proposed method in the case of three economy hotel websites. Finally, Section 5 ends this paper with conclusions and some noteworthy implications.

2. Literature Review

Website service quality (or e-service quality) refers to the quality of the factors presented in the online service environment [2]. Various factors have been identified to evaluate the service quality of hotel websites, such as information value, usability, customer relationship, and service competence.

The main use of a hotel website is to offer hotel information to customers for browsing and searching, thus the information quality is a critical indicator to measure the performance of a hotel website design [17]. Li et al. [18] summarized 16 information features that may drive customers to visit the hotel website. These dimensions include both general travel-related information and hotel reservation information. Usability is considered another important factor in information systems [19]. In the tourism and hospitality industry, researchers have proposed several indicators for measuring website usability. With the rapid development of hotel websites and customers' preferences drift, the information quality is no longer a critical factor for customer satisfaction. By contrast, customer relationship and service competence appear to be core dimensions for hotel websites' service quality evaluation in the existing literature [20]. For example, Tian and Wang [21] examined the effectiveness of electronic customer relationship management (e-CRM) features on hotel websites and found that a well-designed e-CRM system may help less visible hotels gain advantages in the increasingly competitive online marketplace. Hung [22] indicated that hotels should maintain customer relationships by enhancing interactivity and virtual involvement. These two dimensions are also the main distinction between the evaluation systems for e-service quality and website quality although they are correlated [2].

According to the features of different decision tasks, scholars have investigated various linguistic representation tools for information portrayal. Rodríguez et al. [23] first introduced the concept of a hesitant fuzzy linguistic term set (HFLTS) to describe DMs' hesitance among various linguistic terms. However, all the linguistic terms are treated the same which is inconsistent with actual decision scenarios. For example, consider 100 experts are asked to assess the service quality of one hotel website, 40% of them think the performance is good and 60% think the performance is very good. Obviously, the HFLTS can only show the experts' evaluation, that is, between good and very good, but cannot reflect the specific intention of experts. For this issue, Wang et al. [24] combines online reviews and fuzzy theory to develop a decision support model, by utilizing the information of user ratings and text comments. Pang et al. [25] introduced the concept of PLTSs. A PLTSs is composed of two parts: linguistic terms and probabilities of the linguistic terms. The linguistic terms can express the imprecision and vagueness inherent in human judgments. The probabilities of the linguistic terms can characterize the degree of confidence or importance of an individual's evaluation, and can also represent the probabilistic distribution of collective linguistic terms for group evaluation [26]. Therefore, PLTSs regarded as an efficient linguistic information representation tool, has aroused extensive concerns from academics and practitioners [27–30]. This study also uses the PLTSs to interpret and model customers' and hotel managers' collective opinions and takes them as inputs of the proposed hybrid hotel website evaluation method.

Through analyzing similar literature, this study has extracted 4 commonly utilized dimensions with 9 sub-criteria to construct the evaluation system for economy hotel websites' service quality. Table 1 lists the associated dimensions and sub-criteria and their supported references.

Table 1. Dimensions and corresponding sub-criteria for hotel website service quality evaluation.

Customer Dimensions	Symbol	Customer Criteria	References
Customer relationship (D_1)	C_1	Interactivity	(Chou and Cheng, 2012 [31]; Díaz and Koutra, 2013 [1]; Salavati and Hashim, 2015 [20]; Wang et al., 2015 [32])
	C_2	Virtual involvement	
Information value (D_2)	C_3	Completeness	(Bai et al., 2008 [33]; Hung, 2017 [22]; Jeong et al., 2005 [34])
	C_4	Relevance	
	C_5	Timeliness	
Service competence (D_3)	C_6	Responsiveness	(Chou and Cheng, 2012 [31])
	C_7	Empathy	
Usability (D_4)	C_8	Ease of use	(Giannopoulos and Mavragani, 2011 [35]; Jeong et al., 2005 [34]; Ting et al., 2012 [36])
	C_9	Navigability	

3. Method

In this section, we first provide the problem statement and propose an improved distance measure of PLTSs. Based on the new distance measure, we extend the traditional ANP method into the PLTSs context. We further propose an integrated TODIM-PROMETHEE II method to determine alternative ranking with consideration of DMs' psychological behavior.

For the multi-experts MCDM problem with a hierarchical criteria system, we suppose that there are m candidate alternatives A = {A_1, A_2,..., A_m}, which are evaluated over a hierarchical criteria system. Let the hierarchical criteria system contain a set of N dimensions, denoted as D = {D_1, D_2,..., D_N}, and each dimension D_i contains K_i sub-criteria with $\sum_{i=1}^{N} K_i = n$, where n denotes the total number of sub-criteria C = {C_1, C_1,..., C_n}. Let E = {e_1, e_2,..., e_h} denote the set of h DMs. Through consulting DMs' collective opinions, the decision matrix under each sub-criterion can be elicited as $R = \left(r_{ij}\right)_{m\times n}$ with PLTSs, where r_{ij} denotes a probabilistic linguistic evaluation of alternative A_i under sub-criterion C_j. Therefore, the task of this multi-expert MCDM problem is defined as determining an alternative ranking list using the proposed method.

3.1. The Improved Distance Measure between Two PLTSs

Drawing on the idea of an enhanced TOPSIS method, we propose a novel distance measure between PLTSs by fusing the effects of both the positive- and negative-ideal PLTSs.

Definition 1. Let $S = \{s_i | i = 0, 1, 2, \ldots, 2g,\ g \in \mathbb{N}\}$ be a linguistic term set (LTS) with odd cardinality, where s_i is a possible value for a linguistic variable. It satisfies the following requirements: (1) the set is ordered: $\alpha \le \beta \Leftrightarrow s_\alpha \le s_\beta$; and (2) the negation operator of s_α is: $neg(s_\alpha) = s_{2g-a}$.

Definition 2. Let $S_1(p) = \{s_i(p_i) | s_i \in S, \sum_{i=1}^{n} p_i = 1\}$ be normalized PLTSs, $S^-(p) = \{s_0(1)\}$ and $S^+(p) = \{s_{2g}(1)\}$ are the smallest and largest PLTSs, respectively. The distance measure between $S_1(p)$ and $S^-(p)$ is defined as:

$$d^-\left(S_1(p), S_1^-(p)\right) = \left(\sum_{i=1}^{n} |f(s_0) - f(s_i)|^r \cdot p_i^r\right)^{\frac{1}{r}} \tag{1}$$

similarly, the distance measure between $S_1(p)$ and $S^+(p)$ is defined as

$$d^+\left(S_1(p), S_1^+(p)\right) = \left(\sum_{i=1}^{n} |f(s_{2g}) - f(s_i)|^r \cdot p_i^r\right)^{\frac{1}{r}} \tag{2}$$

where p_i means the probability of the linguistic term s_i, f refers to the linguistic scale function (LSF), which reflects the preference of the decision-makers when they are using the linguistic terms, r is a parameter of distance measure and all the elements in $S_1(p)$ are sorted by the value of probability p_i in a descending order.

Definition 3. Let $S_1(p) = \{s_i(p_i)|s_i \in S, \sum_{i=1}^{n} p_i = 1\}$ be a normalized PLTSs, then the relative distance measure of $S_1(p)$ to the largest PLTSs is defined as:

$$d(S_1(p)) = \alpha d^-\left(S_1(p), S^-(p)\right) + (1-\alpha)\left(1 - d^+\left(S_1(p), S^+(p)\right)\right) \quad (3)$$

where α represents the relative importance of the separations of $S_1(p)$ from the smallest PLTSs $S^-(p) = \{s_0(1)\}$ and the largest PLTSs $S^+(p) = \left\{s_{2g}(1)\right\}$, and its value is between 0 and 1. Particularly, when the parameters $\alpha = 0.5$ and $r = 1$, Equation (3) reduces to $d(S_1(p)) = d^-(S_1(p), S^-(p))$ which is the same as Wang [37].

Definition 4. Let $S_1(p) = \{s_i(p_i)|s_i \in S, \sum_{i=1}^{n} p_i = 1\}$ and $S_2(p) = \{s_j'(p_i)|s_j \in S, \sum_{j=1}^{n} p_j = 1\}$ be two normalized PLTSs, and their elements are arranged by the values of s_i and s_j in descending orders, respectively. Then, the distance measure between $S_1(p)$ and $S_2(p)$ is defined as

$$D(S_1(p), S_2(p)) = |d(S_1(p)) - d(S_2(p))| \quad (4)$$

the newly proposed distance measure of PLTSs is different from previous researches. In Wang et al. [37], the distance measures between PLTSs did not consider the impact of the smallest PLTSs, namely, $S^-(p) = \{s_0(1)\}$. By contrast, our proposed distance measures considered both the smallest and largest PLTSs in S. Moreover, this measure balanced the separations of the PLTSs $S_1(p)$ from the positive- and negative-ideal PLTSs through an appropriate fusion strategy. Specifically, this study regards the distance between the normalized PLTSs $S_1(p)$ and the smallest PLTSs $S^-(p)$, namely $d^-(S_1(p), S^-(p))$ as a benefit criterion while the distance measure $d^+(S_1(p), S^+(p))$ as a costly one. In this regard, we propose a novel relative distance measure of $S_1(p)$ to the largest PLTSs by considering the relative importance of two separate measures and the normalization functions of the cost and benefit criteria. Finally, a generalized distance measure related to parameters α and r, as shown in Equation (4), is proposed in this paper.

3.2. Probabilistic Linguistic ANP

Traditionally, there are two types of aggregation strategies in AHP or ANP-based group decision-making: aggregation of individual judgments and aggregation of individual priorities. The former first aggregate a group members' judgments into a new pairwise comparison judgement matrix for the group and generate priorities for alternatives, while the latter first generates the priority vector for each individual, and then aggregate these priority vectors into the priorities of the alternatives for the group. No matter in what stage the aggregation occurs, precise judgments from DMs are widely used in previous studies which may hinder the applications of both methods. To tackle this challenge, Escobar and Moreno-jiménez [38] proposed a novel aggregation of individual preference structures (AIPS) to deal with multi-actor decision-making with AHP.

Different from the traditional ANP technique [6], probabilistic linguistic ANP proposed in this study transforms experts' views on comparative information between dimensions and sub-criteria into PLTSs to better describe human hesitation and uncertainty. There are two levels in the probabilistic linguistic ANP module, namely, the control level and the network level. At the control level, the goal of identifying the weights of dimensions and sub-criteria that impact the objective is set before the process starts. Then, customer surveys and literature reviews are conducted to confirm these dimensions and sub-criteria. At the network level, the interrelationships within each dimension are identified from experts' opinions.

According to the network structure where all elements can communicate with each other, the pairwise comparison matrix among dimensions is constructed as $A^i \in \mathbb{R}^{N \times N}$

$(i = 1, 2, \ldots, N)$, and the pairwise comparisons among sub-criteria in each dimension is formulated as $B^k \in \mathbb{R}^{K_i \times K_i}$ $(i = 1, 2, \ldots, N, k = 1, 2, \ldots, K_i)$, where K_i indicate the number of sub-criteria in the ith and jth dimension, respectively. To conduct the calculation process of probabilistic linguistic ANP module, we should first transform the PLTS comparison matrices into Saaty scale. To tackle this, the general expectation function of the PLTSs is employed [26] to generate the weighting matrix $\mathbf{A} \in \mathbb{R}^{N \times N}$. Since the expectation values range in [0,1], a conversion function is introduced to derive the Saaty scale. Following [12], check the consistency ratio CR for each comparison matrix which should be less than 0.1. Otherwise, a modification on the matrix is needed. The formula of the expectation function for PLTS is as follows:

$$E(S(p)) = \sum_{i=1}^{n} (f(s_i) \cdot p_i) \tag{5}$$

where s_i $(i = 1, 2, \ldots, n)$ is a linguistic term in the LTS S with a probability p_i, f means a LSF from the linguistic term set S. More details about the LSF f can be referred from Wang et al. [39] and Pang et al. [25] for the definition and properties of PLTS. Afterwards, the probabilistic linguistic ANP module can be performed using the decision support software, namely, Super Decisions 3.2 (https://superdecisions.com, accessed on 18 September 2022) and the overall priorities of sub-criteria can be finally determined from the limited super-matrix.

3.3. An Integrated TODIM-PROMETHEE II

In this subsection, TODIM-PROMETHEE II is used to rank alternatives. Its specific processes are as follows:

Step 1. Acquire the decision matrix $R = (r_{ij})_{m \times t}$.

The decision information with PLTSs should be acquired through consulting target customers and experts. Please refer to Section 4.1 for a detailed information acquisition process.

Step 2. Normalize the decision matrix.

The criteria usually can be categorized into two types, benefit criteria and cost ones. No operation is required on the benefit criteria, while the cost criteria should be transformed into benefit ones to keep the same units and measurements of the criteria. The normalization equations are as follows:

$$neg(r_{ij}) = \left\{ s^{ij}_{2g-\alpha_k} \left(1 - p^{ij}_k\right) \middle| s^{ij}_{2g-\alpha_k} \in S, k = 1, 2, \cdots, \#r_{ij} \right\} \tag{6}$$

$$\widetilde{r}_{ij} = \begin{cases} r_{ij}, & for\ benifit\ criterion\ C_j \\ neg(r_{ij}), & for\ cost\ criterion\ C_j \end{cases}, \quad (j = 1, 2, \cdots, n) \tag{7}$$

where α_k denotes the kth subscript of linguistic term s_k, $s^{ij}_{\alpha_k}$ is the linguistic assessment of the ith alternative under criterion C_j, and $\#r_{ij}$ indicates the number of linguistic terms in r_{ij}.

Step 3. Obtain the TODIM-based closeness coefficient values.

The TODIM-based closeness coefficient equation is as below.

$$I^j_{ik} = \begin{cases} \sqrt{\dfrac{\omega_{ju} D(\widetilde{r}_{ij}, \widetilde{r}_{kj})}{\sum_{j=1}^{n} \omega_{ju}}}, & \widetilde{r}_{ij} \succ \widetilde{r}_{kj}; \\ 0, & \widetilde{r}_{ij} \sim \widetilde{r}_{kj}; \\ -\dfrac{1}{t}\sqrt{\dfrac{D(\widetilde{r}_{ij}, \widetilde{r}_{kj}) \cdot \sum_{j=1}^{n} \omega_{ju}}{\omega_{ju}}}, & \widetilde{r}_{ij} \prec \widetilde{r}_{kj}, \end{cases} \tag{8}$$

where $\omega_{ju} = \frac{\omega_j}{\omega_u}$ and $\omega_u = \max(\omega_j)$, $j = 1, 2, \ldots, n$, $D\left(\widetilde{r}_{ij}, \widetilde{r}_{kj}\right)$ indicates the distance measure between alternatives A_i and A_k under criterion C_j. Particularly, an improved distance measure between two PLTSs is proposed to tackle the drawbacks existed in previous distance measures in Section 3.1. What's more, the closeness coefficient value I^j_{ik} denotes the intensity of the preference degree of alternative A_i over A_k under criterion C_j.

In addition, there are three scenarios in Equation (8): (1) when $\widetilde{r}_{ij} \succ \widetilde{r}_{kj}$, I_{ir}^{j} represents a gain; (2) when $\widetilde{r}_{ij} \sim \widetilde{r}_{kj}$, I_{kr}^{j} denotes a breakeven or nil; and (3) when $\widetilde{r}_{ij} \prec \widetilde{r}_{kj}$, I_{ik}^{j} indicates a loss. Different shapes of the prospect value function in the negative quadrant can be derived from different parameter values of t which mean decay factors toward the loss.

Step 4. Calculate the comprehensive preference index.

The TODIM-based comprehensive preference index $I(A_i, A_k)$ for any pair of alternatives $(A_i, A_k)_j$ $(A_i, A_k \in A)$ can be defined as follows:

$$I(A_i, A_k) = \sum_{j=1}^{n} I_{ik}^{j} \tag{9}$$

obviously, the $I(A_i, A_k)$ represents how strongly alternative A_i outranks alternative A_k under each criterion in C. Evidently, the larger the $I(A_i, A_k)$, the stronger the preference for alternative A_i.

Step 5. Determine the outgoing flow of each alternative.

The outgoing flow of alternative A_i can be aggregated as

$$\varnothing^{+}(A_i) = \sum_{k=1, k \neq i}^{m} I(A_i, A_k) \tag{10}$$

the index $\varnothing^{+}(A_i)$ measures how much alternative A_i outranks all the other alternatives in A and can be interpreted as its comprehensive strength. Therefore, the bigger the outgoing flow $\varnothing^{+}(A_i)$, the better alternative A_i outranks the other alternatives.

Step 6. Determine the incoming flow of each alternative.

The incoming flow is

$$\varnothing^{-}(A_i) = \sum_{k=1, k \neq i}^{m} I(A_k, A_i) \tag{11}$$

the incoming flow denotes the degree to which alternative A_i is dominated by all other alternatives in A, thus reflecting the comprehensive weakness of alternative A_i. Therefore, the smaller the incoming flow $\varnothing^{-}(A_i)$ is, the less likely the other alternatives in A outrank A_i.

Step 7. Calculate the net flow of each alternative.

As a result, the net flow of alternative A_i can be obtained as

$$\varnothing(A_i) = \varnothing^{+}(A_i) - \varnothing^{-}(A_i) \tag{12}$$

index $\varnothing(A_i)$ denotes the difference between the outgoing and incoming flows of alternative A_i, which shows a balance between the comprehensive strength and weakness of alternative A_i.

Step 8. Obtain the complete ranking of alternatives by PROMETHEE II.

PROMETHEE II can determine a complete ranking of alternatives $\{\succ, \sim\}$ through the comprehensive net flows $\varnothing(A_i)$. That is,

1. $A_i \succ A_k$. (i.e., A_i outranks A_k) if $\varnothing(A_i) > \varnothing(A_k)$ or
2. $A_i \sim A_k$ (i.e., A_i is indifferent to A_k) if $\varnothing(A_i) = \varnothing(A_k)$.

Clearly, the priority of alternative A_i improves as the value of the net flow $\varnothing(A_i)$ increases.

The overall process of the proposed method can be illustrated in Figure 1 and summarized as three phases:

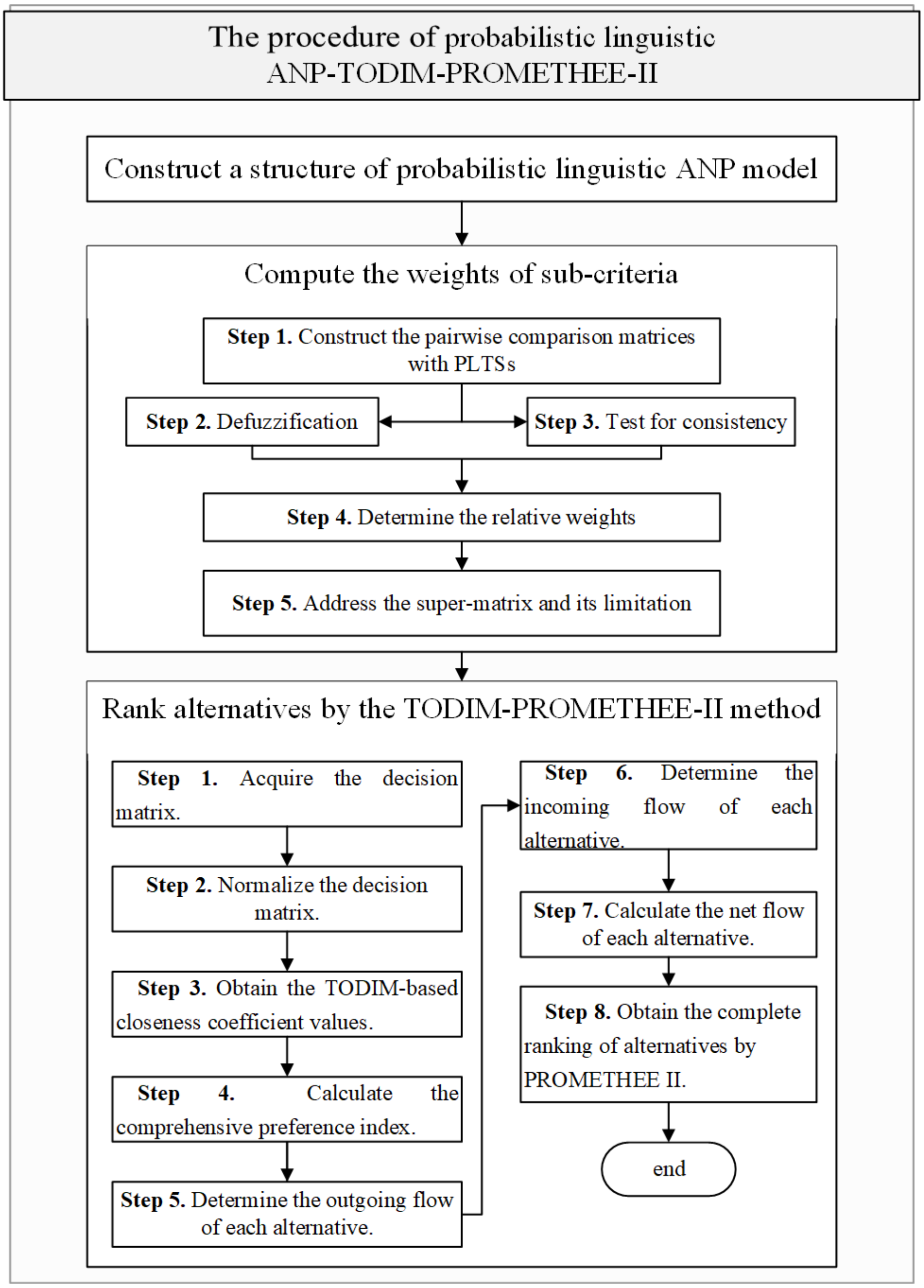

Figure 1. Overall framework of the proposed method.

Phase 1: Construct a structure of probabilistic linguistic ANP module.

Analyze the research problem, determine the dimensions and sub-criteria, then determine the control level and network level of the probabilistic linguistic ANP model in the context of the research.

Phase 2: Compute the weights of sub-criteria.

The weights of sub-criteria are obtained by the super decisions (https://superdecisions.com, accessed on 18 September 2022) which involve five steps: construct the pairwise comparison matrices with PLTSs; defuzzification; test for consistency; determine the relative weights of sub-criteria; and address the super-matrix.

Phase 3: Rank alternatives by the TODIM-PROMETHEE II method.

Get the decision matrix and calculate the net flow of each alternative and obtain the ranking of alternatives using the TODIM-PROMETHEE II method.

4. An Illustrative Application Case

This section evaluates the service quality of three economy hotel websites (7 days, Home Inns, and Hanting Hotel) in Changsha, China. The priorities of different hotel website features are first identified to contribute to economy hotel website design. Then, a sensitivity analysis is conducted to investigate the influence of different parameters on decision results, along with extended applications of our proposal and comparative analysis to verify the effectiveness and efficiency of the proposal.

4.1. Case Description

7 days, Home Inns, and Hanting Hotel are three leading enterprises in the economy hotel industry in China and have mature website direct-selling channels and large numbers of online members. Therefore, this study chooses these three economy hotel websites as the research objects. To carry out the hotel website service quality evaluation, interviews with Chinese Internet users and academic experts were conducted to obtain collective evaluations on service quality of the above three economy hotel websites. These participants include ten lead users, ten ordinary users and five experts in the hotel industry who are assigned the same decision power. Specifically, all the participants are asked to respectively compare each pair of dimensions and sub-criteria and give their assessments on hotel website service quality performance on a 7-point Likert scale. Table 2 presents the detailed linguistic scales.

Table 2. The linguistic scale for hotel website service quality evaluation and pairwise comparison scale on dimensions and sub-criteria.

Linguistic Variables	Linguistic Variables	Linguistic Terms
Very bad (VB)	Very low (VL)	s_0
Bad (B)	Low (L)	s_1
Slightly bad (SB)	Slightly low (SL)	s_2
Medium (M)	Medium (M)	s_3
Slightly good (AG)	Slightly high (SH)	s_4
Good (G)	High (H)	s_5
Very good (VG)	Very high (VH)	s_6

To obtain the pairwise comparison matrix using PLTSs, experts are first asked to compare each pair of dimensions and sub-criteria according to the linguistic scales shown in the second column of Table 2. Then, the comparison results from experts are gathered and transformed into PLTSs. For example, when comparing the information value and usability, if there are ten experts think the influence degree of information value on the usability is *very low* (s_0), ten other experts think *low* (s_1), and the remaining five experts think *medium* (s_3). Then the comparison information between information value and usability can be transformed into a PLTS $\{s_0(0.4), s_1(0.4), s_3(0.2)\}$. To acquire the evaluations on hotel website service quality performance under each criterion, the participants are firstly asked to observe and mark each website quality item for every economy hotel webpage, then they provide their linguistic assessments to measure the performance of each hotel webpage on every website quality item. For example, to assess the completeness of 7 days website under the information value construct, each participant should check whether the hotel website includes complete information about room, restaurant, conference/banquet hall traffic and some other facilities such as introduction, price, picture and availability and then give an overall linguistic assessment under completeness where s_0 refers to a heavy lack of relevant information on 7 days website and s_6 indicates that the website of 7 days has provided all the valuable information for online users. Considering different participants may provide different linguistic terms to assess the same website quality item due to their differences in cognition and personalized preferences, the interview results can be transformed into PLTSs to depict all the participants' linguistic evaluations on a certain website quality item with consideration of both linguistic terms and their probabilities.

4.2. Solve the Case by the Proposed Method

As described in Section 3.1, the proposed method involves the following three phases:

Phase 1: Construct a structure of probabilistic linguistic ANP module.

The probabilistic linguistic ANP model is constructed as Figure 2. We can see that the goal of the probabilistic linguistic ANP module is to determine the weights of dimensions and sub-criteria. Moreover, there are interrelationships and feedback among these dimensions and sub-criteria.

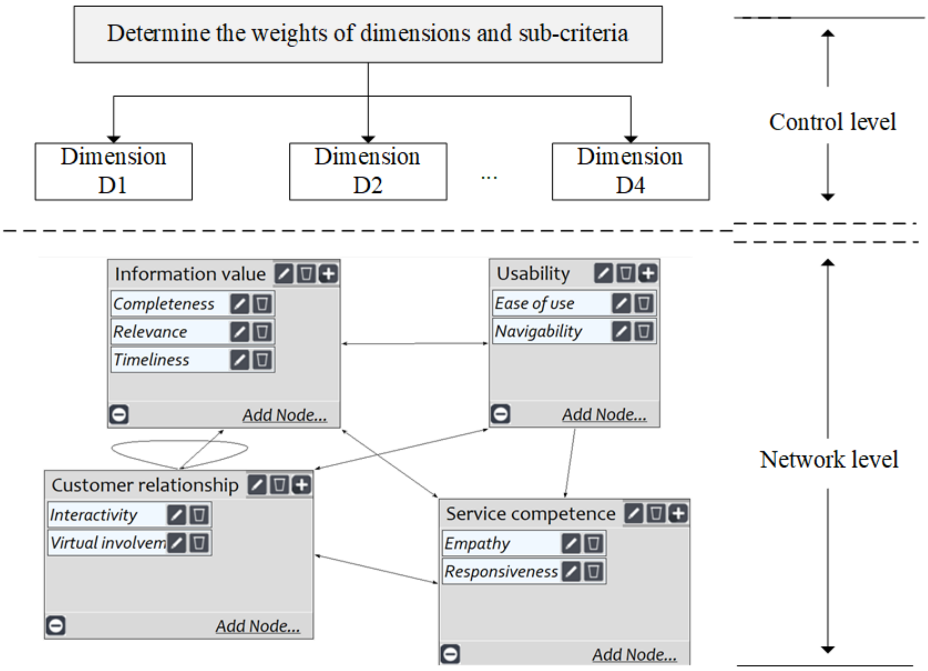

Figure 2. The probabilistic linguistic ANP model for hotel website service quality evaluation.

Phase 2: Compute the weights of sub-criteria.

In this phase, the proposed probabilistic linguistic ANP model is applied to derive the weights of sub-criteria. For doing so, the comparison matrices with PLTSs $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$ $i = (1,2,\cdots,N)$ can be first acquired by transforming the group of experts' qualitative opinions, where $S\left(a^i_{kj}\right)$ indicates a PLTS that measures the differences between the influence degree of dimension D_k on D_i and the influence degree of D_j on D_i. If $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$ is completely or acceptably consistent, the priority vector of $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$, denoted by $\mathbf{w}_i = (w_{i1}, w_{i2}, \cdots, w_{iN})^T$, can be calculated by the eigenvalue method. Otherwise, an adjustment on $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$ is needed. Based on this line of thought, the probabilistic linguistic comparison matrices $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$ $i = (1,2,\cdots,N)$ are gathered by consulting the expert committee. To save space, an example of $\boldsymbol{A}^1 = \left(S\left(a^1_{kj}\right)\right)_{N\times N}$ is shown in Table 3.

Table 3. Comparison results among dimensions with respect to D_1.

$\mathbf{D_1}$	$\mathbf{D_1}$	$\mathbf{D_2}$	$\mathbf{D_3}$	$\mathbf{D_4}$
D_1	$\{s_3(1)\}$	$\{s_2(0.7), s_3(0.3)\}$	$\{s_2(0.3), s_3(0.7)\}$	$\{s_1(0.4), s_2(0.6)\}$
D_2	$\{s_3(0.3), s_4(0.7)\}$	$\{s_3(1)\}$	$\{s_3(0.5), s_4(0.5)\}$	$\{s_1(0.4), s_2(0.6)\}$
D_3	$\{s_3(0.7), s_4(0.3)\}$	$\{s_2(0.5), s_3(0.5)\}$	$\{s_3(1)\}$	$\{s_1(0.6), s_2(0.4)\}$
D_4	$\{s_4(0.6), s_5(0.4)\}$	$\{s_4(0.6), s_5(0.4)\}$	$\{s_4(0.4), s_5(0.6)\}$	$\{s_3(1)\}$

To derive the priority vector of sub-criteria, the PLTSs in comparison matrices $\boldsymbol{A}^i = \left(S\left(a^i_{kj}\right)\right)_{N\times N}$ and super-matrix W should be first transformed into crisp values by Equation (5), and further transformed into values in a 1–9 scale. The super-matrix W is shown in Table 4. Then, check the CR for this matrix which should be less than 0.1. If so, the priority vector of sub-criteria $\omega = (\omega_1, \omega_2, \cdots, \omega_n)^T$ can be computed by Super decisions and the final results are exhibited below.

Table 4. Limited super-matrix W.

		$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	$\mathbf{C_4}$	$\mathbf{C_5}$	$\mathbf{C_6}$	$\mathbf{C_7}$	$\mathbf{C_8}$	$\mathbf{C_9}$
D_1	C_1	0.2085	0.2085	0.2085	0.2085	0.2085	0.2085	0.2085	0.2085	0.2085
	C_2	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
D_2	C_3	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
	C_4	0.194	0.194	0.194	0.194	0.194	0.194	0.194	0.194	0.194
	C_5	0.0315	0.0315	0.0315	0.0315	0.0315	0.0315	0.0315	0.0315	0.0315
D_3	C_6	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	C_7	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172
D_4	C_8	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069
	C_9	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011

The weight vector of the sub-criteria is calculated as $\omega = (0.2085, 0.076, 0.028, 0.0194, 0.0315, 0.21, 0.172, 0.069, 0.011)^T$. We can see that the responsiveness is the most important sub-criteria for hotel websites' service quality, followed by the interactivity and relevance. These above three sub-criteria belong to the service competence, customer relationship and information value constructs, respectively, and their cumulative weight value reaches 0.6125. Moreover, the cumulative weight of the first three constructs (service competence, customer relationship and information value) is 0.92. It suggests that giving more investments on service competence and customer relationship for hotel website design can help hotels gain advantages in the increasingly competitive online marketplace. In addition, although the information value construct is not as central to websites design as it used to be, it is still very important for customers' satisfaction, and it can be regarded as one must-be website feature. This is to say, the presence of an information value construct does not contribute that much to customer satisfaction, but it will remarkably result in customer dissatisfaction if it is absent. These findings can help hotel managers or website designers better recognize customer needs and develop resource allocation plans to meet these needs.

Phase 3: Rank alternatives by the TODIM-PROMETHEE II method.

Step 1. Acquire the decision matrix $R = \left(r_{ij}\right)_{m\times t}$.

According to the linguistic variables shown in the first column of Table 2, the experts and customers committee evaluates three economy hotel websites' service quality on each sub-criterion and the evaluation results are transformed into PLTSs and presented in Table 5.

Table 5. Evaluation results of each economy hotel website under each sub-criterion.

	7 Days (A_1)	Home Inns (A_2)	Hanting Hotel (A_3)
C_1	$\{s_4(0.7), s_3(0.2), s_1(0.1)\}$	$\{s_3(0.45), s_2(0.25), s_1(0.3)\}$	$\{s_3(0.3), s_2(0.2), s_1(0.5)\}$
C_2	$\{s_5(0.6), s_4(0.4)\}$	$\{s_3(0.2), s_2(0.3), s_1(0.5)\}$	$\{s_2(0.5), s_1(0.5)\}$
C_3	$\{s_4(0.4), s_3(0.3), s_2(0.2), s_1(0.1)\}$	$\{s_4(0.2), s_3(0.5), s_2(0.1), s_1(0.2)\}$	$\{s_4(0.6), s_3(0.4)\}$
C_4	$\{s_4(0.6), s_3(0.4)\}$	$\{s_4(0.3), s_3(0.35), s_2(0.35)\}$	$\{s_4(0.5), s_3(0.3), s_2(0.1), s_1(0.1)\}$
C_5	$\{s_3(0.5), s_2(0.5)\}$	$\{s_3(0.3), s_2(0.3), s_1(0.4)\}$	$\{s_3(0.4), s_2(0.5), s_1(0.1)\}$
C_6	$\{s_3(0.5), s_2(0.5)\}$	$\{s_3(0.6), s_2(0.4)\}$	$\{s_4(0.2), s_3(0.8)\}$
C_7	$\{s_6(0.7), s_5(0.3)\}$	$\{s_3(0.5), s_2(0.5)\}$	$\{s_4(0.5), s_3(0.5)\}$
C_8	$\{s_3(0.7), s_2(0.2), s_1(0.1)\}$	$\{s_4(0.1), s_3(0.5), s_2(0.2), s_1(0.2)\}$	$\{s_3(0.3), s_2(0.2), s_1(0.5)\}$
C_9	$\{s_3(0.35), s_2(0.45), s_1(0.2)\}$	$\{s_4(0.15), s_3(0.3), s_2(0.25), s_1(0.3)\}$	$\{s_4(0.2), s_3(0.35), s_2(0.45)\}$

Step 2. Normalize the decision matrix.

Considering all the sub-criteria are benefit types, there is no need for normalization.

Step 3. Obtain the TODIM-based closeness coefficient values.

According to Equation (8), the TODIM-based closeness coefficient values with respect to each sub-criterion can be computed.

Step 4. Calculate the comprehensive preference index.

According to Equation (9), the comprehensive preference index between each pair of alternatives can be derived as $I(A_1, A_2) = -0.3556$, $I(A_1, A_3) = -2.8595$, $I(A_2, A_1) = -8.2555$, $I(A_2, A_3) = -6.1276$, $I(A_3, A_1) = -6.6813$, $I(A_3, A_2) = -1.8954$.

Step 5. Determine the outgoing flow of each alternative.

According to Equation (10), the outgoing flow of alternative A_i can be aggregated as $\phi^+(A_1) = -3.2151$, $\phi^+(A_2) = -14.3831$, and $\phi^+(A_3) = -8.5767$.

Step 6. Determine the incoming flow of each alternative.

According to Equation (11), the incoming flow of each alternative can be generated as $\phi^+(A_1) = -14.9368$, $\phi^+(A_2) = -2.251$, and $\phi^+(A_3) = -8.9871$.

Step 7. Calculate the net flow of each alternative.

According to Equation (12), the net flow of each alternative can be determined as $\phi(A_1) = 11.7217$, $\phi(A_2) = -12.1320$, $\phi(A_3) = 0.4104$.

Step 8. Obtain the complete ranking of alternatives by PROMETHEE II.

Based on the net flows of all alternatives obtained in Step 7, the complete ranking of alternatives is obviously $A_1 \succ A_3 \succ A_2$. Therefore, the service quality of the 7 days website is optimal among all the candidates.

4.3. Sensitivity Analysis

The proposed method in this paper involves a series of parameters that may affect the selection of the optimal economy hotel website. To check the effect of each parameter on the evaluation result, we conduct a sensitivity analysis by changing the parameter values of f, α, r and t, respectively, where f indicates the LSFs, α and r denote two parameters involved in the novel distance measure of PLTSs, and t represents the decay factor toward the loss in TODIM technique. The results are shown in Figures 3–5.

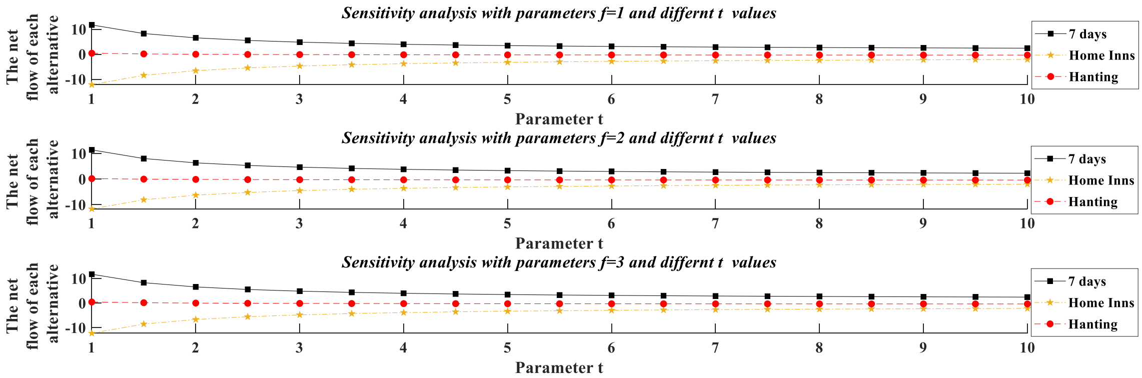

Figure 3. Sensitivity analysis with parameters f and t.

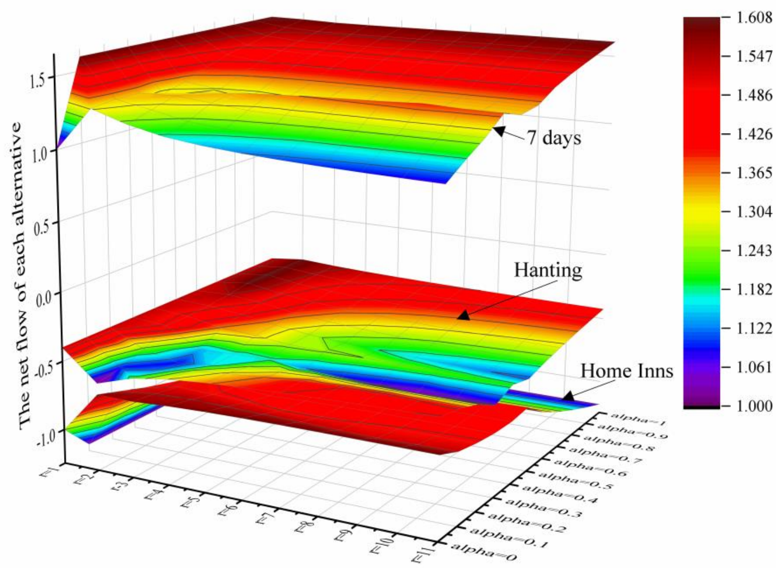

Figure 4. Sensitivity analysis with parameters α and r.

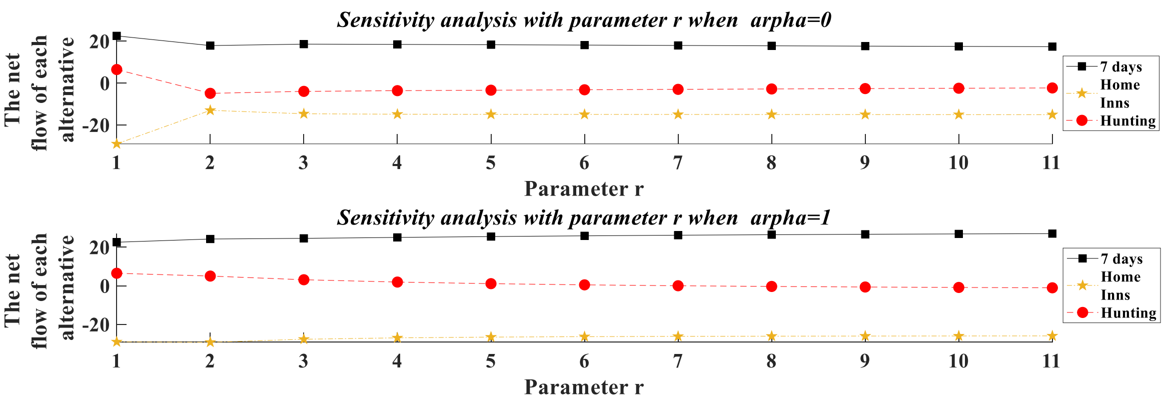

Figure 5. Sensitivity analysis with parameter r when $\alpha = 0$ and 1, respectively.

As depicted in Figures 3 and 4, we can clearly see the ranking results among the three economy hotel websites remain $A_1 \succ A_2 \succ A_3$ regardless of changes in the parameter values of f, α, r and t. Specifically, all the y-axes in Figures 3 and 4 represent the net flow of each alternative. In Figure 3, the x-axes of three sub-figures indicate the values of parameter t which was searched from 1 to 10 under three LSFs ($f \in$ {1, 2, 3}), respectively. In Figure 4, two parameters α and r in the new distance measure are investigated under [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1] and [1–11], respectively, where the LSF is fixed as f = 1. Overall, the sensitivity analysis results confirm that our proposed method is competent and stable when evaluating the service quality of economy hotel websites.

4.4. Comparative Analysis

We introduce five MCDM methods with PLTSs as the baselines to demonstrate the superiority and efficiency of the proposed method and present the comparative results in Figure 6.

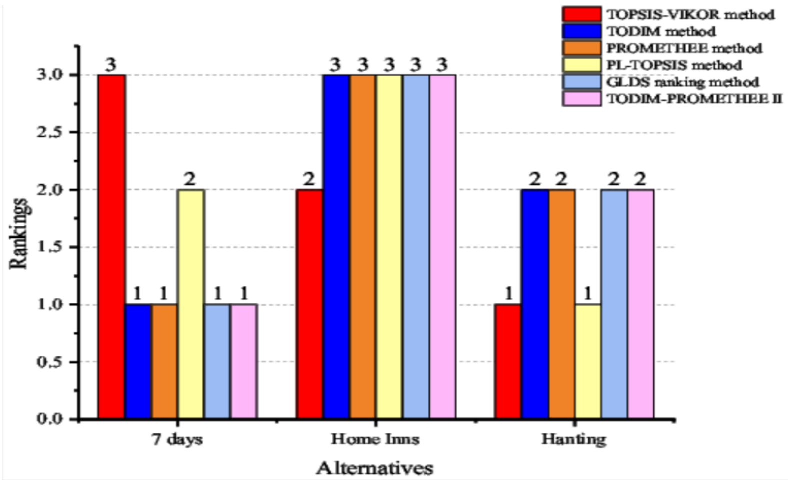

Figure 6. Rankings of the economy hotel websites with different methods. (Note: "1, 2 and 3" indicate the order of preference, that is, "1" is the primary choice, "2" is the secondary choice, and "3" is the last choice.)

TOSIS-VIKOR method [37]: an integrated method by combining two typical reference point-based methods (i.e., TOPSIS and TODIM) for MCDM. The main idea of these two methods is to choose a compromise solution which is nearest to the positive ideal solution and furthest from the negative ideal solution.

TODIM method [37]: a traditional pairwise comparison method that ranks alternatives according to the overall dominance of each alternative over the others under different criteria.

PROMETHEE II method [23]: an extended PROMETHEE II method with PLTSs that utilized an improved possibility degree formula to model the preference function.

PL-TOSIS method [6]: an extended TOPSIS method with PLTSs that used an improved closeness coefficient consistent index to rank alternatives.

The gained and lost dominance score (GLDS) method [7]: the most similar method to our proposal which proposed novel operations of the PLTSs based on the adjusted rules of PLTSs and the LSFs for semantics of linguistic terms so as to avoid information loss, and rank alternatives with consideration of both the "group utility" and the "individual regret" values.

Figure 6 depicts that different ranking results can be obtained via different comparative methods. These differences in ranking results are mainly due to two factors: (1) operations of PLTSs and (2) alternative ranking methods. Next, we will explain the reasons for ranking differences and verify the effectiveness and superiority of our proposal from these two aspects.

(1) Comparison with different PLTS operations. The operations and comparison methods between two PLTSs in works [6,23] are based on the assumption that both PLTSs should have the same number of probabilistic linguistic elements, so extra elements should be added to the PLTS with fewer elements before operations. Moreover, the operations on PLTSs directly multiply the subscripts of linguistic terms by their associated probabilities. However, the linguistic terms and their associated probabilities in PLTSs are two absolutely different dimensions. Therefore, such operations may result in some unreasonable results in some special situations. For example, when calculating the sum of two PLTSs with only one element $S_1(p) = \{s_5(1)\}$ and

$S_2(p) = \{s_4(1)\}$ in a LTS S = $\{s_0, s_1, \ldots, s_6\}$, it is clear that the operated value is 5 × 1 + 4 × 1 = 9, which has exceeded the bound of the given LTS S, thus some linguistic information will be lost in results. Actually, different linguistic terms in PLTSs may have different semantics. To tackle this problem, The GLDS ranking method in Wu and Liao [26] introduced adjusted rules of PLTSs and LSFs for semantics of linguistic terms to improve the operations of PLTSs. In the GLDS method and our proposal, the operations of PLTSs share the same idea and the ranking of alternatives are both obtained by outranking methods. Therefore, the ranking results turn out the same by these two methods. This could be evidence for the rationality and efficiency of our proposal. However, the adjusted rules of PLTSs in Wu and Liao [26] limit in complex calculations and time consuming because one PLTS must be adjusted into different forms when they are compared with different PLTSs.

(2) Comparison with different alternative ranking methods. The TOPSIS-VIKOR and TODIM method in Wang et al. [37] are two popular distance-based ranking methods in decision-making. However, the distances used in Wang et al. [37] did not consider the separations of the PLTS from its corresponding positive- and negative-ideal PLTSs simultaneously, thus information loss may be caused. Moreover, the TODIM method is a single alternative ranking method which failed to consider the degree to which an alternative is dominated by all other alternatives. Our proposal alleviates this potential defect through combining TODIM with the PROMETHEE II method.

Overall, the proposed TODIM-PROMETHEE II method has three advantages than previous ranking methods. First, the improved distance measures of PLTSs can take into account both the differences in semantics and the separations of a PLTS from the positive- and negative-ideal PLTSs, thus it can alleviate the defects of information loss and distortion. Second, the integration of TODIM and PROMETHEE-II can take merits of both comparison-based methods and yield the same decision results with the GLDS, but require fewer computation costs. Third, the design of parameters involved in our proposal can provide DMs with a certain amount of decision flexibility. For example, by virtue of α and r, DMs can choose different distance measures of PLTSs according to practical decision scenarios.

5. Conclusions, Implications and Future Studies

This study proposes a hybrid multi-experts MCDM method with PLTSs to evaluate the service quality of economy hotel websites. Instead of using a single MCDM method to rank alternatives, this method combines merits of both TODIM and PROMETHEE II methods to generate alternative ranking. On one hand, it can take DMs' bounded rationality into consideration which is in line with actual decision scenarios. On the other hand, DMs will have more decision flexibility in choosing different distance measures and semantics of linguistic terms, as well as the decay factor which reflects their psychological behaviors. A case study concerning three economy hotel websites evaluation is performed, and the evaluation results and comparative analysis illustrate the efficiency and feasibility of the proposal.

The results of this study have provided both theoretical and practical implications. In theory, the novel distances between PLTSs can effectively compare PLTSs, thus can benefit distance-measure based-MCDM methods with PLTSs. In practical applications, the following suggestions can be provided for hotel website managers: firstly, managers should focus on responsiveness, interactivity and relevance, which account for the highest proportion of the nine criteria; secondly, although 7 days hotel ranks first, it is slightly inferior in terms of completeness, representativeness and navigability, and managers should further improve the service quality of the hotel from these three aspects; thirdly, the last ranked Home Inns is far inferior to other hotels in terms of completeness, relevance, timeliness and empathy, managers should focus on breakthroughs in these four aspects; finally, Hanting Hotel, the second largest hotel in the world, has no characteristics of its own, managers should explore the advantages of the hotel and focus on its development. Moreover, our proposal can also be applied to solve similar multi-expert MCDM problems in many other industries, such as risk evaluation, healthcare management, and tourism management. For example, in the field of tourism, tourists usually choose restaurants among various candidates under a hierarchical criteria system based on a large number of qualitative assessments. Moreover, the integrated criteria are actually interdependent [40]. Therefore, our proposed method can be used to solve such problems.

However, in terms of hotel selection, we used three Chinese hotel websites as our research subjects, which may have some research errors, and subsequent studies can further explore more hotel selection in depth. In addition, we chose only one metric and did not consider similarity metric and likelihood metric.

For future study, other information measures of PLTSs, such as similarity measures and likelihood measures, can be investigated to extend the probabilistic linguistic decision theory. Furthermore, we will explore how to adjust the hybrid probabilistic linguistic ANP-TODIM-PROMETHEE II method to other practical multi-experts MCDM problems, such as healthcare management, service failure detection and hotel recommendations.

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