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Research Article

A Dynamic Product Evaluation Model Based on Online Customer Reviews from the Perspective of the Elaboration Likelihood Model

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Plenty of online customer reviews (OCRs) provide consumers with an abundant source of word-of-mouth (WOM). It makes potential customers evaluate alternative products or services more conveniently. Thus, relative studies have been arising. Considering that existing research is almost deployed from the perspective of reviewers, the study proposes an evaluation model based on the OCRs from the view of potential customers. In the model, the OCRs in text form are translated into probabilistic linguistic term sets from the perspective of the cognitive process model, namely, the elaboration likelihood model, for further evaluation. Meanwhile, the influence of the OCRs' published time is also taken into consideration, and then, the model is transformed into a dynamic evaluation model. In general, we propose a dynamic product evaluation model to simulate the cognitive process of the potential consumers disposing of OCRs. In addition, an evaluation of 6 hotels in Chengdu, Sichuan Province, is developed based on the proposed dynamic product evaluation model, and some discussions, as well as conclusions, are also carried out.

1. Introduction

Online customer review (OCR) is a type of word-of-mouth (WOM) also called electronic word-of-mouth (e-WOM), sprang up in the age of the Internet [1]. They are usually published online by people who have purchased products/services or people who have experience using them. The OCRs provide potential customers with a more extensive and convenient way to acquire WOM of objective products/services. The rich information on product/service attributes and qualities contained in OCRs can alleviate information asymmetry in the online market [2], while the Internet provides customers with a persistent platform to exchange their experiences and evaluations of products/services [3]. Meanwhile, records can be retained for an extremely long time. In contrast, traditional WOM expressed in face-to-face communication is restrained in objects and propagation scopes. The traditional way to express opinions makes WOM spread in a limited social group, while whoever searches the Internet has the chance to read comments and have access to e-WOM provided by other Internet users.

Customer-generated OCRs can be obtained and utilized by potential consumers, sellers, and producers [4]. Sellers can utilize the OCRs to predict sales, while producers could make observations of customers' satisfaction and expectation based on the OCRs to improve products/services. Potential customers usually search and read OCRs before making purchase decisions. The purpose is to make more comprehensive knowledge of the products/services from the experience of purchased customers, except for the description and pictures published online by manufacturers or sellers. A large number of studies show that OCRs do affect customers' purchase intention, and the previous research mainly focused on detecting how OCRs affect customers' purchase intention and what factors matter in the decision-making process [5–7]. There are also studies on the evaluation of product quality [8, 9], service quality [10], and consumer satisfaction [11]. Most of them are conducted from the perspective of consumers who have purchased products/services, and it provides a perspective to observe the customers' responses or requirements and even to make an evaluation of products. Customers make a purchase decision based on their demands and take the OCRs as references. The evaluation of products/services forms based on their cognitive process of received information. Thus, it is important to research how potential customers process these OCRs, further forming their own opinions and evaluating the performances of products/services in the way which the potential consumer process information contained in OCRs.

To fill the gap, this study proposes a model to depict the cognitive process of information contained in OCRs when potential consumers receive information. Product evaluation is launched from the view of potential consumers. From the perspective of the elaboration likelihood model (ELM), the dynamic product evaluation model is established. Besides, the probabilistic linguistic term sets (PLTSs) are utilized to express the linguistic information contained in the OCRs, which makes the operation easier. The main contributions can be concluded as follows:

(1) A product evaluation procedure model is established based on how potential consumers form their opinions on products/services. Different from the previous research which is proposed from the reviewers' perspective, this paper is conducted from the perspective of potential customers who are also the information receivers on how they form evaluations on an objective commodity. It provides a new perspective to utilize OCRs to make evaluations or decisions. Besides, it also can be beneficial for Internet platforms, sellers, and producers to control and utilize reviews.

(2) The ELM is used to explain the cognitive process of customers and establish a corresponding mathematical model. This paper imports the ELM with a central route and a peripheral route to show the cognitive process of customers in dealing with OCRs. Furthermore, a mathematical model is provided to finish the computation.

(3) Taking the time factor of OCRs into consideration, the importation of publishing time makes the evaluation procedure more complete and more accurate. The OCRs published at different times have different influences on evaluations; thus, they are given different importance degrees, which construct the dynamic evaluation procedure.

(4) Expressing linguistic information with PLTSs facilitates the operation and computation. Translating OCRs in linguistic form into PLTSs in a mathematical version reflects the different strengths of positive and negative reviews, as well as the quantity and quality of the arguments in the reviews. In this way, the information in OCRs is expressed as comprehensively as possible.

Based on the purpose, the construction of this paper is organized as follows: Section 2 reviews the related literature involved in OCRs. Section 3 introduces some basic knowledge of ELM, multicriteria decision-making (MCDM), and PLTS. Section 4 makes a detailed description of modeling the dynamic product evaluation. In Section 5, the proposed model is applied to solve a practical problem of evaluating the quality of hotels based on OCRs and some discussions are also developed. In the end, some conclusions are drawn in Section 6.

2. Literature Review

The boom of OCRs has attracted the attention of many scholars and generated plentiful relative research. The studies on OCRs are mostly concentrated on evaluating consumers' satisfaction [11–15], product quality [8, 9], and service quality [16–18] with the aim of improvement or sales [19]. More specifically, OCRs can help classify customers' requirements and enhance product design [20]. Meanwhile, there are also some studies focusing on assessing the quality of OCRs from the perspective of review usefulness/helpfulness [21–24], credibility [25–27], and so on. In addition, technologies such as machine learning, text mining, and opinion mining are applied in the research of OCRs [28–32]. The main business applicable scenarios of the research change from online sales [33, 34] and box office [35] to the hospitality industry [36–38].

The research evaluating service quality and satisfaction based on OCRs mainly concentrated on identifying attributes that would affect the perceptive service quality of consumers [39]. Bogicevic et al. [31] employed data-mining techniques and logistic regression to evaluate the service quality of passenger airlines and identified the most discussed themes among OCRs and the most significant predictors of airline WOM. Lim and Lee [17] explored the significant dimensions of service quality for the full-service carriers and the low-cost carriers in airline travel, respectively. In the hospitality industry, service attributes [40] and factors influencing consumers' perceived indoor environment quality [29] were analyzed based on OCRs. Customers' satisfaction and their influence factors are also explored by OCRs [11, 12, 41]. The studies mentioned above evaluated the perceived quality and satisfaction of the consumers who have bought services, but not the perception of the potential consumers who have read the OCRs.

There are also research studies developed from the perspective of potential consumers, and most of them detected the influence factors of the consumer's perceived helpfulness or usefulness based on the "help vote" provided by potential consumers. Some of them took the "help vote" result provided by the website into use [21, 22, 42], while some others designed a questionnaire to investigate the perceptive helpfulness/usefulness of potential consumers [43, 44]. The research was developed from different perspectives and mainly focused on the characteristics of reviews but had no consensus on the determinants or attributes of review helpfulness. Meanwhile, these studies failed to examine review helpfulness/usefulness considering the information processing of consumers.

As the perception of review helpfulness is the outcome of the consumers' information process, a dual process theory ELM is frequently used [45]. Based on the ELM, both the characteristics of reviews and reviewers on review helpfulness have been analyzed [45–49]. Wang and Karimi [45] found that the use of first-person singular pronouns had a negative impact on the perceived helpfulness of OCRs and that this kind of influence was moderated by other review attributes. Zhu et al. [46] researched the direct influence of reviewer credibility (including reviewer expertise and reviewer online attractiveness) and the moderating effects of the service price and rating extremity on perceived OCR helpfulness. How did the writing style, especially review readability and sentimental tone properties, and the attributes of OCR like its comprehensiveness, clarity, and relevance to the product/service experience affect perceived helpfulness was also researched [47, 48]. The positive effect of review consistency (i.e., the level of consistency between a review text and its attendant review rating) on review usefulness was revealed [49]. There was also other research that was developed on ELM to study the influence factors of review credibility [25, 50, 51], review adoption [52–54], purchasing intention [55, 56], and collective decision [57]. The argument quality was proved to be significant in influencing review credibility [50, 51]. Focused on different aspects, the determinants of review adoption were discussed. Cheung et al. [52] found comprehensiveness and relevance to be the most two effective components of the argument quality, which made them the key influencers of information adoption. Meanwhile, the argument quality and the argument perspective were considered to have a positive effect on a perceived value and have a further influence on the adoption of OCRs, while the argument quality was confirmed to be positively associated with information credibility and quantity sufficiency [53]. The studies by Park et al. [56] and Lee [55] revealed that both the argument quality and quantity of OCRs had a positive influence on purchasing intention of online shoppers, while low-involvement consumers were more affected by quantity rather than the quality of reviews when high-involvement consumers were exactly the opposite.

The existing literature from the perspective of ELM only measured which factors are important in relative information processing results and how significant these factors are but did not describe how these factors affect evaluation formation and what the outcomes are. This paper is to solve this problem and show the information process of potential consumers on OCRs and the corresponding evaluation outcomes. Another issue of these studies is how to measure the quality and the characteristics of the OCRs. They distinguished the review valences into positive, neutral, and negative only, ignoring the different intensities of positive and negative reviews. To deal with this, this paper imports PLTSs to measure the orientation and strength of the sentiment expressed in reviews more accurately.

3. Theoretical Foundation

3.1. The ELM. Dual process theories, which have the most influential impact on persuasion and attitude change, explain how the content and context of the message affect the message credibility in two different types of information processing. The most typical and prominent two models of dual process theories are the heuristic-systemic model (HSM) [58] and the ELM [59].

The HSM divides information processing into a heuristic one and a systematic one. In the systematic information process, the receiver tends to pay considerable cognitive efforts to analyze the validity of the message by evaluating the consistency of the message's arguments and conclusions. By contrast, people who take the heuristic process depend more on noncontent cues to access the validity of the message and therefore to decide whether to accept the conclusion of the message. The heuristic process is much easier and effortless than another one in the cognitive process. Petty and Cacioppo indicated that the information process of the recipient can be included in the central route and peripheral route and proposed the ELM [60]. The careful and logical consideration of information was taken in the central route, while the attitude changed or the decision was made just based on the simple and superficial cues in the peripheral route. The HSM and the ELM are similar in information processing and attitude change, and even Chaiken has noted that the central route encompasses her systematic view of persuasion, while the peripheral route encompasses her heuristic view of persuasion, although the latter "is not synonymous with the peripheral route since the peripheral label is also used to refer to classical and operant conditioning models of attitude change as well as persuasion approaches which focus on motivational orientations not addressed by the heuristic/systematic framework" [60].

In the theory of ELM, the elaboration likelihood plays a very important role, which directly influences the route that the subject chooses to process information. When the elaboration likelihood is high, persuasion is about to occur in the central route, and on the contrary, the peripheral route would be followed when the elaboration likelihood is low. The elaboration likelihood is influenced by the motivation and ability to process the information of the recipient. Only if the information processing motivation and ability of the subject is high, the elaboration likelihood is high. When either the motivation or the ability is low, the elaboration likelihood is low. Although the motivation and the ability of the recipient have an impact on the elaboration likelihood, it is apparent that information is to be processed in a central route only when both the motivation and ability to process the information of the subject are high. A simplified flowchart is pictured in Figure 1 to exhibit the persuasion process of the ELM.

3.2. MCDM and PLTS. MCDM is an efficient method for finding the optimal solution or choice among multiple alternatives by evaluating the performance of alternatives'

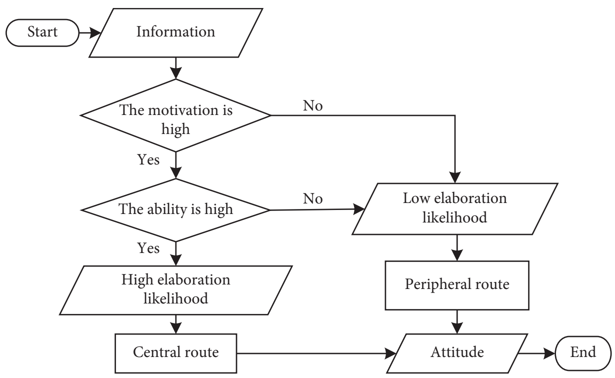

Figure 1: The process of the ELM.

multiple criteria. Alternatives are comprehensively assessed from multiple criteria. In general, an MCDM problem can be concisely expressed in a matrix [61]: $D = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array}$, where $A = \{A_i \mid i = 1, 2, \cdots, m\}$ is the set of alternatives, $C = \{C_j \mid j = 1, 2, \cdots, n\}$ is a set of criteria, and x_{ij} is the performance of the alternative A_i with respect to the criterion C_j. The weight of the criteria can be expressed as $W = \{w_1, w_2, \cdots, w_n\} = \{w_j \mid j = 1, 2, \cdots n\}$.

In some real-life decision-making situations, information cannot be expressed precisely in a quantitative form but can only be expressed in a qualitative form, which arises the necessity and usefulness of linguistics approaches. Herrera and Herrera-Viedma [62] gave a framework that contains steps to follow in solving the MCDM problem under linguistic information and pointed out that the linguistic approach gives a more flexible and highly beneficial framework to deal with decision-making problems using qualitative information when the performance values cannot be expressed by numbers. The PLTS is an effective linguistic approach in depicting linguistic information (e.g., taking the form of linguistic terms) and different importance degrees (e.g., taking the form of the probability distribution) simultaneously. Pang et al. [63] proposed the concept of PLTS and gave its definition.

Definition 1 (see [63]). Let S be a linguistic term set (LTS), and a PLTS can be expressed as follows:

$$L(p) = \left\{ L^{(l)}\left(p^{(l)}\right) \middle| L^{(l)} \in S, p^{(l)} \geq 0, \sum_{l=1}^{\#L(p)} p^{(l)} \leq 1 \right\}, \quad (1)$$

where $L^{(l)}(p^{(l)})$ denotes the lth linguistic term $L^{(l)}$ associated with the probability $p^{(l)}$ and $\#L(p)$ is the number of different linguistic terms in $L(p)$. As the linguistic evaluation scale, the LTS S can take the form of $S = \{s_{-\tau}, \cdots, s_{-1}, s_0, s_1, \cdots, s_\tau\}$ and $S = \{s_0, s_1, \cdots, s_\tau\}$ (τ is a positive integer) [64]. For the convenience of computing, $L^{(l)}(p^{(l)})$ $(l = 1, 2, \cdots, \#L(p))$ in $L(p)$ are arranged according to the subscripts of $L^{(l)}$ $(l = 1, 2, \cdots, \#L(p))$ in descending order.

Note that if $\sum_{l=1}^{\#L(p)} = 1$, then the complete probabilistic distribution information of all the linguistic terms in $L(p)$ is obtained, if $\sum_{l=1}^{\#L(p)} < 1$, then there exist some limitations of knowledge, and the normalized PLTS (NPLTS) denoted as $\overline{L}(p) = \left\{L^{(l)}(\overline{p}^{(l)}) \mid L^{(l)} \in S, \overline{p}^{(l)} > 0, \sum_{l=1}^{\#L(p)} = 1\right\}$ can be obtained by the equation $\overline{p}^{(l)} = (p^{(l)}/\sum_{l=1}^{\#L(p)} p^{(l)})$ $(l = 1, 2, \cdots, \#L(p))$; if $\sum_{l=1}^{\#L(p)} = 0$, then there is lack of the probability information, and PLTSs degrade into hesitant fuzzy linguistic term sets (HFLTSs). Wu et al. [64] defined the expectation function of PLTSs as follows.

Definition 2 (see [64]). Let $S = \{s_\alpha \mid \alpha = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$ be a subscript-symmetric addictive linguistic evaluation scale and $L(p) = \left\{L^{(l)}(p^{(l)}) \mid L^{(l)} \in S, p^{(l)} \geq 0, \sum_{l=1}^{\#L(p)} p^{(l)} \leq 1\right\}$ be a PLTS; then, the expected value function of $L(p)$ is as follows:

$$E(L(p)) = \frac{\sum_{l=1}^{\#L(p)} \left(\left(\left(\alpha^{(l)} + \tau\right)/2\tau\right) p^{(l)}\right)}{\sum_{l=1}^{\#L(p)} p^{(l)}}, \quad (2)$$

where τ is a positive integer, $L^{(l)}(p^{(l)})$ denotes the lth linguistic term $L^{(l)}$ with the corresponding probability $p^{(l)}$, $\alpha^{(l)}$ is the subscript of $L^{(l)}(p^{(l)})$, and $\#L(p)$ is the number of different linguistic terms in $L(p)$.

4. The Construction of the Dynamic Product Evaluation Model

A dynamic product evaluation model is constructed in this section, and three main subsections are included: the customer cognitive process that depicts the cognitive information processing of customers from the perspective of ELM, the dynamic evaluation procedure that mainly shows the dynamic process in evaluation considering time factors, and the dynamic product evaluation model is established to delicately demonstrate the integrated dynamic procedure in evaluating the product.

4.1. The Customer Cognitive Process. The dual process theory is a cognitive psychology theory that provides comprehensive information on how individuals process information, establish validity assessments, and later form decision outcomes [65]. In the environment of the Internet, customers usually take descriptions, pictures, and OCRs concerning products as references before making their purchase decisions. Consumers' information processing of OCRs enables them to evaluate products/services before making purchase decisions [66]. To simulate consumer information processing, we utilize one of the classical models of dual process theory, i.e., ELM, to model the individual cognitive processes of OCRs. We assume that these customers who read the OCRs have the motivation and ability to process product evaluation information; otherwise, there is no need for them to take time and effort on it. Thus, the central route is the cognitive way when recipients process the evaluation information contained in OCRs in this paper.

In the central route of ELM, the argument quantity and quality are thought to be the two main influence factors [67]. The argument quantity is the number of arguments in the OCR, and recipients are more prone to adopt the one with more arguments in quantity [67]. The argument quantity can be counted in an easy way. Specifically, a review of one criterion can be taken as one argument; thus, the argument quantity of an OCR can be calculated based on how many criteria are contained in it. The argument quality reflects its strong and compelling degree and is constructed by argument strength and valence [68]. In previous research studies, the strength of the argument represents the sentiment strength and the argument valence represents sentiment orientation in the argument [69]. Furthermore, it was thought that strong argument messages generated more positive cognitive responses than those with weak argument information did [69]. However, the strength and valence of the argument should be combined because they work together to influence the recipient's cognitive processing simultaneously. It should be noted that the argument with a positive valence stimulates positive cognitive processing, while the negative argument has a totally opposite effect. Meanwhile, the stronger the positive (or negative) argument is, the stronger the positive (or negative) cognitive effort is. That is, a strong and negative argument more tends to motivate stronger negative cognitive processing than a weak and negative argument. When measuring the argument quality, the argument valence and argument strength should be discussed in combination.

In conclusion, the customer's cognitive process on OCRs from the perspective of ELM can be summarized as follows: first, it evaluates the argument quantity of OCRs based on the number of the mentioned criteria. Then, it measures the quality of the argument from the perspective of the argument strength and valence, and finally, it evaluates the product and makes a decision based on the comprehensive analysis of the quantity and quality of the argument in OCRs.

4.2. The Dynamic Evaluation Procedure. The OCRs are usually published online at different times and during different periods of products. Customers as the recipient of the information contained in the OCRs are inclining to take the newest OCRs as the most important and credible ones. On the contrary, outdated OCRs are less considered when evaluating or making decisions. The study has found that the latest reviews have a significant impact on determining sales because they minimized the mental effort required by consumers in reading and processing a large number of reviews [70]. The OCRs with different posting times have different influences on the evaluation results, and thus, their important degrees are also differentiated. Considering the dynamic characteristic of the time, a dynamic evaluation procedure model is proposed to reflect its different important degrees.

Suppose that the publishing times of OCRs are separated into k periods, and $T = \{t_z \mid z = 0, 1, 2, \cdots, k\}$ is taken to present different time nodes and time sequence, in which t_0 is the oldest one and t_k is the newest. λ_0 is denoted as the time coefficient of the period $[t_0, t_1]$, and the time coefficient of the period $[t_z, t_{z+1}]$ can be expressed as $\lambda_z = \lambda_0 + \lambda_0 \cdot \varepsilon \cdot z = (1 + \varepsilon z)\lambda_0$ (ε can take different values depending on the actual condition). The evaluation of OCRs should be performed by multiplying by the corresponding time coefficient. Taking $S = \{s_z \mid z = 0, 1, \cdots, k-1\}$ as the evaluation result in different periods (s_0 is the initial evaluation result of the first period $[t_0, t_1]$, and s_z is the result of the zth period $[t_z, t_{z+1}]$), the calculating result should be $R_0 = s_0\lambda_0 + s_1\lambda_1 + \cdots + s_{k-1}\lambda_{k-1} = s_0\lambda_0 + s_1(1+\varepsilon)\lambda_0 + \cdots + s_{k-1}\{1+\varepsilon(k-1)\}\lambda_0 = \sum_{z=0}^{k-} 1 s_z(1+\varepsilon z)\lambda_0$. To eliminate the influence of different time lengths, the sum of the time coefficient $\sum_{z=0}^{k-1}[(1+\varepsilon z)\lambda_0]$ should be divided. Thus, the final evaluation result after considering the influence of time and removing the influence of time length is $R = (R_0/\sum_{z=0}^{k-1}(1+\varepsilon z)\lambda_0) = (\sum_{z=0}^{k-1}s_z(1+\varepsilon z)\lambda_0/\sum_{z=0}^{k-1}(1+\varepsilon z)\lambda_0)$, which can be simplified as $R = (\sum_{z=0}^{k-1}s_z(1+\varepsilon z)/\sum_{z=0}^{k-1}(1+\varepsilon z))$. It can be inferred from the equation that this model depicts the relative influence and importance of OCRs published in different periods. When there is an extension in the period of time, such as the appearance of the period $[t_k, t_{k+1}]$, the only change to R_0 is to add the corresponding evaluation result of the new increasing period to it (new R_0 can be noted as R_0^N, where $R_0^N = R_0 + s_k\lambda_k = R_0 + s_k(1+\varepsilon k)\lambda_0$), and updated R (noted as R^N) turns into $R^N = (R_0^N/\sum_{z=0}^{k}(1+\varepsilon z)\lambda_0) = (\sum_{z=0}^{k}s_z(1+\varepsilon z)/\sum_{z=0}^{k}(1+\varepsilon z))$ accordingly.

The dynamic evaluation procedure model manifests the influence of the OCRs published at a different time on the evaluation result and quantifies relative importance. Meanwhile, the computation of this model is clear and concise. When a new time period appears, there is no need to recalculate the previous evaluation result concerning the time influence, which greatly reduces the workload and complexity of computation. In addition, this model can also be used to evaluate product performance in different periods with the aim of dynamic management.

4.3. The Dynamic Product Evaluation Model. Based on the above analysis, the customers' cognitive processes in the arguments contained in OCRs are highly consistent with the MCDM model under the probabilistic linguistic circumstance: the MCDM model makes a choice among multiple alternatives based on the performance analysis on diverse criteria, and the customers keep an eye on the argument quantity of OCRs and measure the number of arguments based on the number of mentioned criteria. Thus, the MCDM model is suitable for quantifying the cognitive process of customers. The PLTS, especially the PLTS with a subscript-symmetric additive linguistic evaluation scale (e.g., $L(p) = \left\{L^{(l)}(p^{(l)}) \mid L^{(l)} \in S, p^{(l)} \geq 0, \sum_{l=1}^{\#L(p)} p^{(l)} \leq 1\right\}$, $S = \{s_\alpha \mid \alpha = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$), can be applied to depict the linguistic information contained in OCRs and quantify the argument quality measuring the strength and valence of arguments simultaneously. In the subscript-symmetric addictive PLTS, the plus/minus of α in the linguistic evaluation scale $S = \{s_\alpha \mid \alpha = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$ expresses positive/negative evaluation and the absolute value shows the strength of the corresponding positive/negative evaluation. Thus, the quality of the argument is measured by the use of PLTS.

In the dynamic evaluation procedure model, the OCRs posted at different times are different in importance, and the corresponding evaluation result based on them is multiplied by different influencing factors, which is in accordance with the actual situation. Meanwhile, another realistic phenomenon is that customers also take OCRs with good performance in the argument quantity and quality as important as the newest OCRs. Thus, the time influence factor of these OCRs should be set as same as that of the newest OCRs.

The dynamic product evaluation model is proposed based on the previous analysis, and the main structure of this model is pictured in Figure 2.

From Figure 2, it can be found that five main steps are included in the dynamic product evaluation model. The specific and detailed descriptions of the procedures are explained in the following.

Step 1. Distinguishing all the criteria based on the analysis of OCRs.

Each useful OCR contains several criteria, and all of these criteria consist of the criteria set $C = \{C_j \mid j = 1, 2, \cdots, n\}$, in which n is the number of the total criteria in all the OCRs and each criterion is discriminative with each other.

Step 2. Measuring the argument quality with PLTS to express the linguistic information contained in each OCR.

The symbol O_i is taken to represent the probabilistic linguistic information in the ith OCR, and L_{ij} is the PLTS which expresses the evaluation of the ith OCR concerning the jth criterion. Then, we denote the probabilistic linguistic expression of the information in the ith OCR as $O_i = \{L_{i1}, L_{i2}, \cdots, L_{in}\} = \{L_{ij} \mid j = 1, 2, \cdots, n\}$, where $L_{ij} = \left\{L^{(l)}(p^{(l)}) \mid L^{(l)} \in S, p^{(l)} \geq 0, \sum_{l=1}^{\#L(p)} p^{(l)} \leq 1\right\}$, $i = 1, 2, \cdots, q$, and $S = \{s_\alpha \mid \alpha = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$. If certain L_{ij} is a null set, it means that the OCR contains no evaluation information concerning the criterion.

Considering that nonnull L_{ij} is in the form of a set with not less than one element, equation (2) is used to compute the comprehensive evaluation of L_{ij}, and E_{ij} is taken to represent the corresponding computation result. Let $\widehat{O}_i = \{E_{ij} \mid j = 1, 2, \cdots, n\}$ be the set after computing, and E_{ij} is obtained based on equation (2). The plus/minus of $\overline{\alpha}_{ij}$ expresses the positive/negative sentiment, and the absolute value shows the strength of the corresponding sentiment. E_{ij} of a certain null set L_{ij} is set to be 0.5 (e.g., $E_{ij} = 0.5$, when L_{ij} is a null set), which means that the sentiment orientation concerning the jth criterion is neutral.

Step 3. Calculating the argument quantity of each OCR.

As analyzed in the previous step, $C = \{C_j \mid j = 1, 2, \cdots, n\}$ is the criteria set, and there are n criteria in total. $O_i = \{L_{i1}, L_{i2}, \cdots, L_{in}\} = \{L_{ij} \mid j = 1, 2, \cdots, n\}$ $(i = 1, 2, \cdots, q)$ expresses the linguistic information in the OCR O_i concerning each criterion in the criteria set. The argument quantity of a certain OCR O_i is measured by counting the number of the criteria mentioned in it. The number of nonnull PLTSs L_{ij} is counted as the number of the arguments in OCR O_i and denoted as N_i $(i = 1, 2, \cdots, q)$.

Step 4. Adding into the time influence factor according to the quantity and quality of the arguments.

Considering the influence of time, the time coefficient is added to the evaluation model, and the dynamic evaluation procedure model is proposed in Section 4.2. Besides, customers prefer to believe and apply the OCRs with high quantity and high quality in arguments; thus, these OCRs should be beyond the influence of time and taken as important as the newly published OCRs. In addition, the OCRs concerning different criteria may have differences in the argument strength and valence; thus, it is reasonable to consider this. Based on this, the PLTSs of OCRs' criteria with high quantity and quality in arguments are given the same time coefficient as the newest OCRs. O_i^H and O_i^O are used to symbolize the OCR with high quantity and high quality synchronously and others, separately. The rules of distinguishing the PLTSs of the OCRs with high quantity and high quality are shown as follows:

$$O_i = \begin{cases} O_i^H, \text{when } N_i \geq \lceil n/2 \rceil \text{ and } \exists E_{ij} \subset [0, 0.25] \cup [0.75, 1], \\ O_i^O, \text{when } N_i < \lceil n/2 \rceil \text{ or } \forall E_{ij} \subset (0.25, 0.75), \end{cases} \tag{3}$$

where N_i $(i = 1, 2, \cdots, q)$ is the quantities of the arguments in the ith OCR, $i = 1, 2, \cdots, q$ is the number of OCRs, n is the number of the criteria, and E_{ij} is the expectation value of the PLTS L_{ij}.

The time coefficient of O_i varies accordingly. The time coefficient of the newest OCRs is assigned to the OCRs O_i^H, while the time coefficients of the OCRs O_i^O comply with the rule in Subsection 4.2. We suppose that the OCRs are divided into k periods by the time node set $T = \{t_z \mid z = 0, 1, 2, \cdots, k\}$. Taking λ_0 as the time coefficient of the period $[t_0, t_1]$, the time coefficient of the period $[t_z, t_{z+1}]$ can be expressed as $\lambda_z = \lambda_0 + \lambda_0 \cdot \varepsilon \cdot z = (1 + \varepsilon z)\lambda_0$ and the time coefficient of the latest period $[t_{k-1}, t_k]$ can be expressed as $\lambda_{k-1} = \lambda_0 + \lambda_0 \cdot \varepsilon \cdot (k-1) = [1 + \varepsilon(k-1)]\lambda_0$. The time coefficient of the OCRs is set as $\lambda_{k-1} = [1 + \varepsilon(k-1)]\lambda_0$, no matter when they are published. Meanwhile, the time coefficient of the OCRs O_i^O is assigned

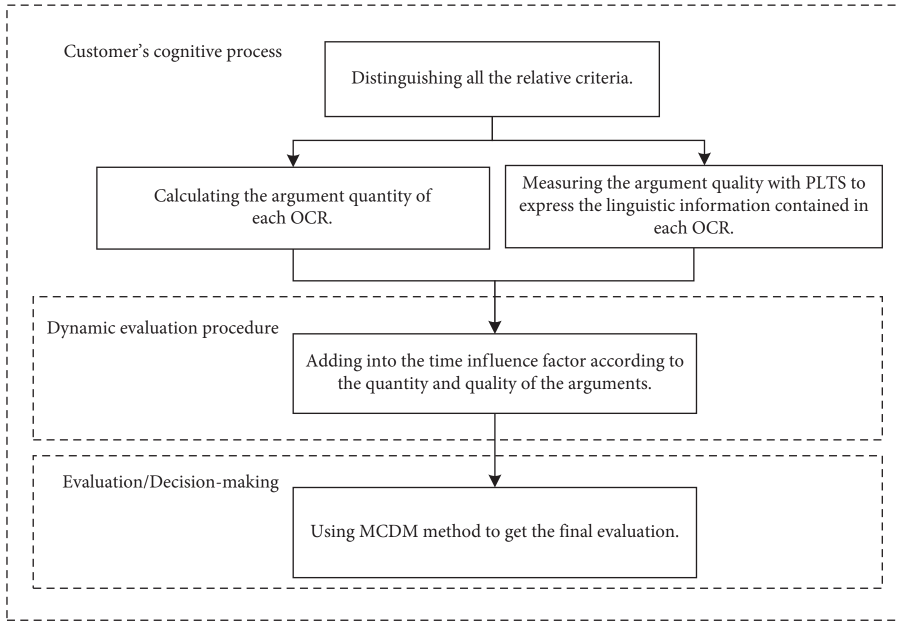

Figure 2: The structure of the dynamic product evaluation model.

according to their published periods. The specific classification is shown in the following equation:

$$\lambda_i = \begin{cases} \lambda_{k-1}, \text{when the OCR is } O_i^H \\ \lambda_z, \text{when the PLTS is } O_i^O \end{cases}, z = 0, 1, 2, \cdots, k, \quad (4)$$

where k is the number of the periods and z is the period in which the OCRs O_i^O are posted. Following Example 1 is to show the above specific process.

Example 1. We take $C = \{C_j \mid j = 1, 2, \cdots, 5\}$ as a criterion set of alternatives in A, and O_1 is one of the OCRs published online. We suppose that the PLTSs with $S = \{s_\alpha \mid \alpha = -3, \cdots, -1, 0, 1, \cdots, 3\}$ of each criterion are $L_{11} = \{2_{(0.5)}, 3_{(0.5)}\}$, $L_{12} = \{0_{(0.2)}, 1_{(0.7)}, 3_{(0.1)}\}$, $L_{13} = \{\}$, $L_{14} = \{1_{(0.3)}, 2_{(0.5)}, 3_{(0.2)}\}$, and $L_{15} = \{\}$, respectively.

Thus, we have $O_1 = \{\{2_{(0.5)}, 3_{(0.5)}\}, \{0_{(0.2)}, 1_{(0.7)}, 3_{(0.1)}\}, \varnothing, \{1_{(0.3)}, 2_{(0.5)}, 3_{(0.2)}\}, \varnothing\}$. L_{13} and L_{15} are null sets, which is because there is no evaluation of the performances of the criteria C_3 and C_5 in the OCR O_1. We have $E_{11} = 0.917$, $E_{12} = 0.667$, $E_{13} = 0.5$, $E_{14} = 0.817$, and $E_{15} = 0.5$, and thus, $\widehat{O}_1 = \{0.917, 0.667, 0.5, 0.817, 0.5\}$. The sentiment orientation of the OCR O_1 concerning the criteria C_1, C_2, and C_4 is positive, and the expected sentiment values are 0.917, 0.667, and 0.817, respectively. There is no evaluation message concerning the criteria C_3 and C_5 contained in the OCR O_1, and their corresponding sentiment orientations are thought to be indifferent. Furthermore, we have $N_1 = 3$; there are 3 nonnull PLTSs in OCR O_i,and the PLTSs L_{13} and L_{15} concerning criteria C_3 and C_5 are null sets.

We suppose that the OCRs are published in the periods of $[t_0, t_1]$, $[t_1, t_2]$, $[t_2, t_3]$, and $[t_3, t_4]$, and λ_0 is the time coefficient of the period $[t_0, t_1]$. If OCRs O_1^H and O_2^O are both published in the period $[t_1, t_2]$, then the time coefficient of O_1^H is $\lambda_1 = (1 + 3\varepsilon)\lambda_0$ (in consistent with the OCRs published in the period $[t_3, t_4]$), while the time coefficient of O_2^O is $\lambda_2 = (1 + \varepsilon)\lambda_0$.

Step 5. Using the MCDM method to obtain the final evaluation.

Based on the previous procedures, the linguistic information contained in the OCRs is presented in the form of PLTSs and the time coefficient is obtained. Then, a certain MCDM method can be chosen to derive the final evaluation result. Because the assessment of products is given from the perspective of different criteria, we can not only get the comprehensive evaluation of the products but also get the performance of them on a certain criterion by synthesizing the customer' evaluation. It is more convenient for product promotion.

To illustrate the computation procedure clearly, a data flowchart is presented in Figure 3.

5. Implementation and Discussions

In this section, a comparative analysis of 6 hotels in Chengdu, Sichuan Province, is conducted based on the proposed dynamic product evaluation model, which illustrates the effectiveness of the model to some extent. Meanwhile, some comparisons and discussions are also presented.

5.1. Case Study. As a widely used website for searching, reserving, and commenting on travel destinations and hotels, TripAdvisor is a great source of OCRs. It provides travelers (i.e., customers) a platform to express their opinions of hotels and researchers a plenty source of data to study. The analysis of this case is based on OCRs and relative information concerning 6 hotels in Chengdu, Sichuan Province in China, crawled from TripAdvisor. In the following, the detailed process is described.

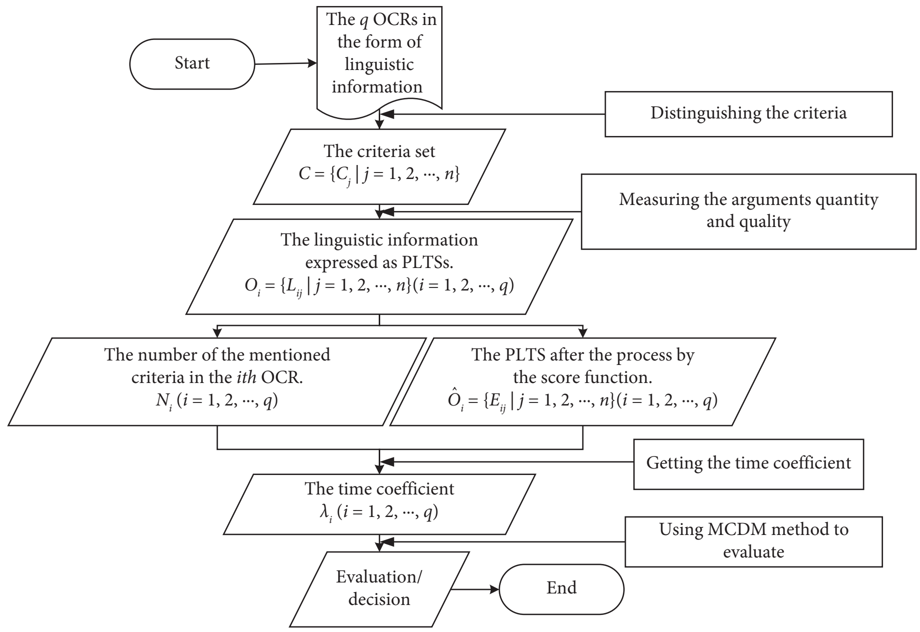

Figure 3: The data flowchart of the dynamic product evaluation model.

Table 1: The criteria and their keyword sets.

Criteria	Keywords
Location (C_1)	Distance, walking, location, road, metro, walk, street, bridge, river, heart, downtown, area, city, station, subway, stop, Tianfu square, Chunxi road, Chengdu museum, city center, located in downtown, metro station, minute walk, subway station, . . .
Service (C_2)	Staff, manager, reception, hospitality, service(s), front desk, experience, guest service, service manager, customer service, room service, housekeeping, . . .
Room (C_3)	Room(s), amenities, home, bed(s), suite, bedroom, apartment, size, feel at home, feel like home, . . .
Views (C_4)	View(s), place, city, river, floor, corner, bridge, view(s) of the city, river view, city view, view(s) of the river, . . .
Foods (C_5)	Buffet, breakfast, lunch, dinner, cafe, dishes, food, restaurant, meal, dining, snacks, drinks, fruit, dishes, . . .
Facilities (C_6)	Pool, swimming, gym, sauna, park, mall, shower, tub, bath, bathroom, toilet, TV, kitchen, dryer, washer, Wi-Fi, Internet, massage, spa, laundry, hotel facilities, steam room, washing machine, massage chairs, laundry services, smoking room, . . .

5.1.1. Step 1: Crawl and Preprocess the OCRs and Relative Information from TripAdvisor. The OCRs and relative information of 6 hotels in Chengdu, such as the reviews, the title of the review, the date of the review, and the date of stay, are crawled from TripAdvisor. There are 3,522 reviews being downloaded and 3,444 reviews left for research after the preprocessing of deleting the reviews which are reduplicative or with special and unidentifiable symbols. In detail, there are 647 reviews of Temple House (A_1), 604 reviews of Ritz-Carlton, Chengdu (A_2), 479 reviews of the InterContinental Global Centre (A_3), 291 reviews of JW Marriott Hotel, Chengdu (A_4), 542 reviews of the InterContinental Residences Chengdu City Center (A_5), and 881 reviews of Shangri-La Hotel, Chengdu (A_6).

5.1.2. Step 2: Distinguish the Criteria and Obtain the PLTSs and Time Coefficient. WordStat, text analysis software, is the application program used in this paper to extract the criteria mentioned in the OCRs. The topics extracted by WordStat refer to the criteria, while the keywords contained in the topics consist of a topic-relative keyword set which can be used to distinguish the criteria in the following step of transforming PLTSs. Based on the extracted keywords and topics, some manual works are performed to make the result more precise. Similar topics are merged into a criterion, while their keyword sets are also merged and reduplicative keywords are eliminated. The extracted 6 criteria and their keywords sets are listed in Table 1.

The transformation of the linguistic information in text form into PLTSs is based on Table 1. StanfordNLP, a natural language processing Python package, is used to analyze the sentiment of reviews. By programming in Python, the PLTS of each review concerning each criterion is extracted and preserved. StanfordNLP distinguishes the sentiment in the text into 5 levels,

TABLE 2: The part of the PLTSs of A_1's reviews concerning each criterion.

$L_{ij}(p)$	C_1	C_2	C_3	C_4	C_5	C_6
O_1	$\varnothing$	$\{s_{-2}(0.018), s_{-1}(0.072), s_0(0.124), s_1(0.499), s_2(0.287)\}$	$\{s_{-2}(0.128), s_{-1}(0.379), s_0(0.305), s_1(0.172), s_2(0.016)\}$	$\varnothing$	$\varnothing$	$\varnothing$
O_2	$\varnothing$	$\{s_{-2}(0.012), s_{-1}(0.070), s_0(0.226), s_1(0.507), s_2(0.185)\}$	$\{s_{-2}(0.009), s_{-1}(0.084), s_0(0.329), s_1(0.514), s_2(0.064)\}$	$\varnothing$	$\{s_{-2}(0.018), s_{-1}(0.072), s_0(0.124), s_1(0.499), s_2(0.287)\}$	$\varnothing$
O_3	$\{s_{-1}(0.001), s_0(0.092), s_1(0.586), s_2(0.321)\}$	$\{s_{-2}(0.018), s_{-1}(0.072), s_0(0.124), s_1(0.499), s_2(0.287)\}$	$\{s_{-2}(0.016), s_{-1}(0.082), s_0(0.195), s_1(0.487), s_2(0.220)\}$	$\varnothing$	$\varnothing$	$\{s_{-2}(0.018), s_{-1}(0.072), s_0(0.124), s_1(0.499), s_2(0.287)\}$
...	...	...	...	...	...	...
O_{646}	$\{s_{-2}(0.069), s_{-1}(0.206), s_0(0.304), s_1(0.393), s_2(0.028)\}$	$\{s_{-2}(0.046), s_{-1}(0.137), s_0(0.205), s_1(0.453), s_2(0.159)\}$	$\{s_{-2}(0.041), s_{-1}(0.143), s_0(0.303), s_1(0.417), s_2(0.096)\}$	$\varnothing$	$\{s_{-2}(0.018), s_{-1}(0.072), s_0(0.124), s_1(0.499), s_2(0.287)\}$	$\varnothing$
O_{647}	$\varnothing$	$\{s_{-2}(0.136), s_{-1}(0.409), s_0(0.287), s_1(0.156), s_2(0.012)\}$	$\{s_{-2}(0.014), s_{-1}(0.093), s_0(0.266), s_1(0.474), s_2(0.153)\}$	$\{s_{-2}(0.026), s_{-1}(0.089), s_0(0.067), s_1(0.639), s_2(0.179)\}$	$\{s_{-2}(0.026), s_{-1}(0.089), s_0(0.067), s_1(0.639), s_2(0.179)\}$	$\varnothing$

correspondingly, expressed as a subscript-symmetric addictive linguistic evaluation scale $S = \{s_\alpha \mid \alpha = -2, -1, 0, 1, 2\}$ in this manuscript, which represent very negative, negative, neutral, positive, and very positive sentiment, respectively. The part of the extraction results of A_1's reviews (i.e., the PLTSs of each criterion) is listed in Table 2.

Then, we calculate the expectation value of each PLTS based on equation (2), count the number of criteria the OCR mentioned, and distinguish the OCRs with high quantity and high quality based on equation (3). The part of the corresponding results is shown in Table 3.

The time spans, during which the reviews are published, are separated into several periods by a year. For example, the reviews of A_1 appeared since 2015; thus, there are 6 periods 2015, 2016, 2017, 2018, 2019, and 2020, respectively. The time coefficient of each review is determined based on Step 4 in Section 4.3 (with $\varepsilon = 1$).

5.1.3. Step 3: Make an Evaluation Based on PLTSs and Time Factors. Based on the previous computational results, a basic and simple MCDM method called the arithmetic weighted average (AWA) is used to get the final evaluation. The results are listed in Table 4, and to make it more explicit, a line chart is presented in Figure 4.

It can be seen from Table 4 and Figure 4 that the comprehensive evaluation result is $A_1 \succ A_5 \succ A_6 \succ A_3 \succ A_2 \succ A_4$, which means that A_1 performs better than any other hotels in this case. In detail, the best performance of criteria location (C_1), service (C_2), and room (C_3) is Temple House (A_1), while Shangri-La Hotel, Chengdu (A_6), has the best view scenery (C_4), the InterContinental Global Centre (A_3) provides the most delicious foods (C_5), and the facilities (C_6) of the InterContinental Residences Chengdu City Center (A_5) are the best. The simple AWA method conducted ignoring the posting time of OCRs results in an assessment of $A_1 \succ A_6 \succ A_5 \succ A_2 \succ A_3 \succ A_4$, while the evaluation result is $A_1 \succ A_6 \succ A_5 \succ A_3 \succ A_2 \succ A_4$ without differentiating OCRs in diversifying quantity and quality. The results indicate that the proposed dynamic model, which accounts for the impact of time factors by assigning varying weights to OCRs published at different periods, does indeed affect the evaluation outcomes. The comprehensive ranking of these 6 hotels is $A_1 \succ A_3 \succ A_6 \succ A_4 \succ A_2 \succ A_5$ on the TripAdvisor website, which is different from the evaluation results in this paper. On the one hand, the TripAdvisor score is assigned by OCR publishers and does not take into account the cognitive information processing of OCRs receivers. On the other hand, the website's evaluation is influenced by reviews written in all languages, whereas our manuscript's evaluation is based solely on English reviews.

5.2. Discussion. The value of ε and the way of dividing the time period have an influence on the time factor, and thus, they have an influence on the final evaluation result. In this subsection, the influence of these changes is discussed and the change of the final result with ε in the determination of the time factor is described first. We set different values of ε as 1, 0.5, 0.1, 0.05, 0.001, 0.005, and 0.001, respectively, to analyze the sensitivity and picture the result in Figure 5.

Table 3: The part of the expectation value of A_1's PLTSs.

E_{ij}	$C = \{C_1, C_2, C_3, C_4, C_5, C_6\}$	N_i	O_i^H / O_i^O
O_1	{0.5, 0.741, 0.392, 0.5, 0.5, 0.5}	2	O_1^O
O_2	{0.5, 0.696, 0.635, 0.5, 0.741, 0.5}	3	O_2^O
O_3	{0.806, 0.741, 0.703, 0.5, 0.5, 0.741}	4	O_3^H
...	...	...	...
O_{646}	{0.526, 0.571, 0.516, 0.5, 0.741, 0.5}	4	O_{646}^O
O_{647}	{0.5, 0.375, 0.665, 0.713, 0.713, 0.5}	4	O_{647}^O

Table 4: The computational results of each hotel.

E_{ij}	C_1	C_2	C_3	C_4	C_5	C_6	F
A_1	0.620	0.679	0.636	0.571	0.608	0.565	0.613
A_2	0.574	0.659	0.617	0.571	0.593	0.551	0.594
A_3	0.551	0.657	0.628	0.549	0.617	0.567	0.595
A_4	0.599	0.634	0.599	0.552	0.578	0.533	0.582
A_5	0.594	0.649	0.632	0.568	0.598	0.593	0.606
A_6	0.595	0.651	0.612	0.592	0.610	0.557	0.603

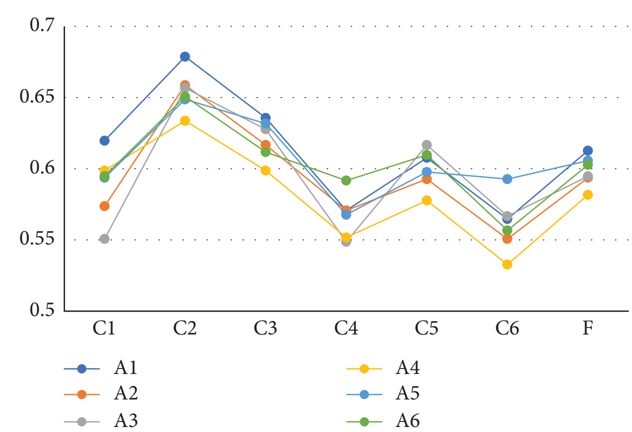

Figure 4: A line chart of the results.

Figure 5 shows that the difference between any two hotels narrows when the value of ε changes from 1 to 0.5. The dominance relation between A_2 and A_3 changes from $A_3 \succ A_2$ to $A_2 \succ A_3$ when the precedence relationship between A_5 and A_6 changes into $A_6 \succ A_5$ from $A_5 \succ A_6$. If the precedence relationship between two hotels remains the same, their gap reduces with the decrease of ε. While the gap between two alternatives increases with the decrease of ε if their precedence relationship changes under some value of ε. The relation between A_2 and A_3, as well as the relation between A_5 and A_6, can be taken as reference. It is reasonable to assume that the final evaluation result changes with the value of ε.

Then, setting the value of ε as 1, we analyze the influence of the different way of dividing the time period on the evaluation result. P_1, P_2, P_3, P_4, and P_5 represent the time period separated by five years, two years, one year, one season, and one month, respectively. The comparative results are illustrated in Figure 6.

With the way of demarcation in time period changes, the calculation and the relative relation among alternatives change. The tendency of this change is not regular in Figure 6, but the value of the computed results with the division

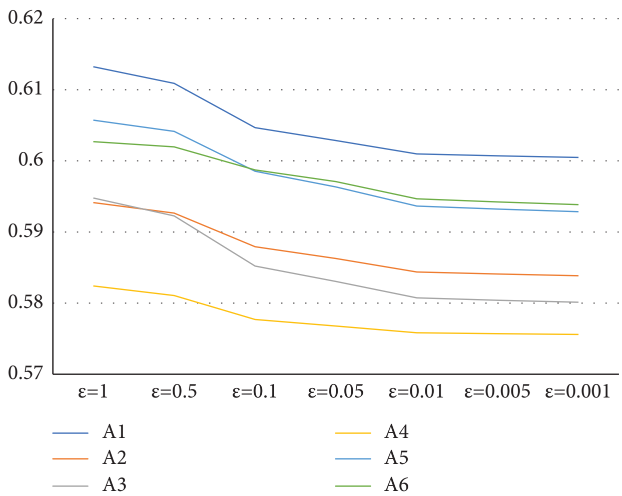

Figure 5: The sensitivity analysis of ε.

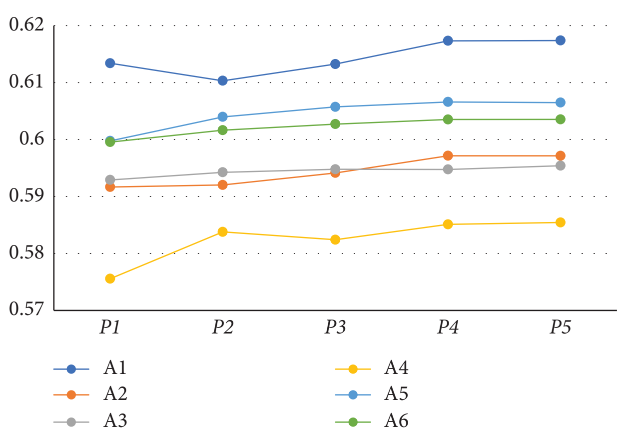

Figure 6: The evaluation under different ways of dividing time periods.

plans P_4 and P_5 is. This might represent that dividing the time period by seasons and months makes no obvious difference on the result. Thus, there is no need to divide the time period by months, because it requires much more computation works than by seasons.

5.3. Managerial Implications. Compared to the traditional approach of analyzing OCRs from the publisher's perspective, the proposed evaluation model utilizes the ELM to consider the receiver's information processing, providing practical implications for managers and online review platform service providers. The model highlights that OCR receivers may have different evaluations than those provided by publishers due to their cognitive information processing, emphasizing the importance for managers to understand how receivers process OCRs and form their evaluations, which can impact potential consumer behavior. In addition, it is crucial for managers and online review platform services to effectively manage the OCRs published at different times, with particular attention given to the most recent reviews. This is because timing can significantly impact the formation of a receiver's evaluation.

6. Conclusions

In order to depict how potential consumers process OCRs in the linguistic version, the ELM is imported and modeled to make evaluation and the PLTSs are transformed from the OCRs for computation. To reflect the difference of the OCRs published at different times, the time factor is developed to describe the dynamic characteristic. Thus, a dynamic product evaluation model is constructed based on the OCRs from the perspective of ELM and potential customers. Furthermore, an evaluation and comparison of 6 hotels is deployed based on OCRs crawled from TripAdvisor to illustrate the proposed model. Some discussions are also conducted concerning the influences of the values of ε and the way of dividing time periods on the evaluation results.

In this study, the product evaluation procedure model is established from the perspective of potential consumers, which is different from previous studies deployed from the perspective of reviewers. Based on the cognitive way, consumers process OCRs and form an impression on products/services, and the model provides a method to evaluate from the view of potential customers. The influence of the posting time of OCRs is taken into consideration, while a mathematical model is constructed to depict the cognitive process of ELM and provides convenience for the following computation. It is found that time factors do matter in the evaluation and have an influence on the final results. Using PLTSs to describe the information contained in the OCRs makes the computation more convenient and accurate. The merchants benefit from this model to evaluate the image of their products/services formed among potential consumers. Moreover, it can also be helpful for managers to predict sales based on the evaluation and to maintain the product/company image by managing the OCRs and taking some intervening measures.

There are also defects in our approach, and we will do much more research in the future. For example, the pattern of the evaluation result changes with the value of ε, and the way of time period partition is an important issue, which is needed for further research. Furthermore, it is hypothesized in this paper that all potential consumers process information through the central route. However, it is possible that some individuals may resort to the peripheral route due to the limited time or ability, which may differ from our hypothesis. Therefore, additional investigation can be pursued in this direction. Meanwhile, if there is a more effective method to weigh the time influence of OCRs, further attention should be given to improve the dynamic product evaluation model.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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