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Closed-form evaluations and open-ended comment options: How do they affect customer online review behavior and reflect satisfaction with hotels?

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A R T I C L E I N F O

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A B S T R A C T

The online review systems of digital platforms feature a variety of designs. This study examines how closed-form evaluations and open-ended textual comment options affect customers' online review writing behaviors and reflect satisfaction with hotels. We find that direct and spillover effects exist. These refer to the effects of customers' closed-form evaluations of a product or service attribute on their reviews of the same attribute and other attributes in their open-ended comments, respectively. Regarding the direct effect, positive closed-form evaluations of attributes reduce customers' behaviors of writing details about the same attributes in open-ended comments, but negative closed-form evaluations of attributes increase that behavior. The increasing effect is greater than the reducing effect. Regarding the spillover effect, closed-form evaluations of certain attributes increase customers' behaviors of writing details about other attributes in open-ended comments. Additionally, we find that the heterogeneity effect lies in the different roles of closed-form evaluations and open-ended textual comments in reflecting customers' overall satisfaction. Open-ended comments about the advantages of the attributes have a more significant effect than the closed-form evaluations of the same attributes in reflecting overall customer satisfaction, but closed-form evaluations better reflect customers' low overall satisfaction with the disadvantages of the attributes. The direct, spillover, and heterogeneity effects on customers' evaluations and comments regarding independent hotels are higher than those effects on evaluations and comments regarding chain hotels. The findings provide insights for companies to design review systems, understand customer perceptions, and use the positive electronic word-of-mouth effect.

1. Introduction

The platform economy, which refers to economic and social activities that are facilitated by digital platforms, has become prosperous with the rapid development of information technology and the growing number of Internet users. Many customers write and post their reviews on digital platforms after conducting online shopping or booking activities [5]. These online reviews feature two aspects of significant value for companies. First, they help managers understand customer perceptions of their consumption experience. Second, they generate electronic word of mouth (eWOM), which refers to the communication among customers or between customers and product or service providers through Internet-based technology that are related to their descriptions or evaluations of their consumption experience [42]. The effect of eWOM on companies' reputation and customer demand has proven to be significant [30]. Thus, utilizing the eWOM effect is one of the key ways for companies to enhance their revenue and achieve better financial performance [28]. This is particularly true for the context of this study, the hotel industry, in which many customers refer to past customers' online reviews to make their online booking decisions [8]. In the hotel industry, eWOM is typically spread through online customer reviews and online recommendations or opinions [18].

Understanding customers' online review behaviors and the reflected satisfaction from their reviews is the first step in utilizing the eWOM effect [28]. However, online customer review behavior is complex. Previous studies (e.g., [56,60]) have examined various factors that influence customers' online review behaviors. These factors include the motivation for customers to write online reviews [56], customers' emotions [60], customers' consumption experience [4], and customers' demographic and online community participation characteristics [84]. However, very few, if any, studies have focused on how the designs of online review systems affect customers' online review behaviors.

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Our study fills this literature gap by examining how customers' online review behaviors and reflected satisfaction from online reviews are affected by the design of the review system, particularly, the open-ended comments and closed-form evaluation options in the hotel industry. Various digital platforms are rapidly emerging and developing today. Many of them provide opportunities for customers to write and post their online reviews. The forms of these reviews can be different, such as open-form comments or closed-form evaluations. In this study, open-form comments refer to online textual comments, which have an open structure that allows customers to provide description or evaluations of hotels in their own words [4,76]. Further, closed-form evaluations refer to ratings or votes for product or service attributes, which only let customers select from limited options such as a number (for ratings) or votes (e.g., "liked" or "recommended"; [6,8]).

The options of giving customers the opportunity to write reviews in an open form, a closed form, or both, as well as the specific formats of these forms, depend on the design of the review systems in the platform [75]. In the hospitality and travel industry, many platforms, such as Yelp for restaurants and Booking.com for hotels, provide options for customers to leave open-form textual comments. Additionally, platforms can allow customers to rate their overall satisfaction or dissatisfaction with certain product or service attributes, such as rooms, locations, and services for hotels on TripAdvisor, or seat comfort, food and beverages, ground services, and cabin staff services for airlines on Skytrax. Further, various platforms offer the opportunity to vote for positive or negative perceptions, such as like or dislike for the product or service attribute of hotels on Expedia, or recommend or do not recommend on Skytrax. In particular, for the hotel industry discussed in this study, analyzing online customer reviews is more challenging because of the various product or services offered as a bundle for customers' consumption [13]. Previous studies of online customer reviews of hotels focused on the determinants of customer ratings (e.g., [59]) and the contents and linguistic characteristics of textual reviews (e.g., [84,85]). However, the literature on how the review options of closed-form evaluations or open-ended comments affects online customer review behavior is still lacking.

The objective in this study is to examine how customers' closed-form evaluations affect their open-form comments and to compare the roles of closed-form evaluations and open-ended textual comments in reflecting customers' overall satisfaction with their consumption experience. Therefore, we raise four research questions. The first two research questions focus on customer review behavior. We want to examine direct and spillover effects. The direct effect refers to the effect of customers' closed-form evaluations of a product or service attribute on their review behaviors regarding the same attribute in their open-ended comments. Thus, our first research question is: how do the closed-form reviews of an attribute affect customers' review writing behaviors in their open-ended textual comments about the same attribute? In addition, the spillover effect refers to the effect of customers' closed-form evaluations of a product or service attribute on their review behaviors regarding other attributes in their open-ended comments. Accordingly, the second research question is: how do the closed-form reviews of an attribute affect customers' review writing behaviors in their open-ended textual comments about the other attributes? Further, we also want to the compare the roles of closed-form evaluations and open-ended textual comments in reflecting customers' overall satisfaction, namely, the heterogeneity effect. Therefore, our third research question is: how do attribute-level closed-form evaluations and open-ended textual comments reflect customers' overall satisfaction? Last, various providers, depending on how they are categorized (i.e., chain versus independent), may have different brand effects, operational procedures, or other features that may not be familiar to customers [45]. Thus, the information posted online regarding chain versus independent providers (i.e., hotels in this study) may contain different levels of ambiguity. Online customer reviews may reflect these different levels of ambiguity and customers' efforts to reduce such ambiguity by providing more information. Therefore, our fourth research question is: how does the category of the hotels (i.e., chain or independent) affect the above-mentioned direct, spillover, and heterogeneity effects on customers' online reviews? To examine the above research questions, we collected data from two popular booking and review websites in the hotel industry: Expedia.com and Booking.com. We used text mining approaches to analyze online customer reviews.

The contributions of this study lie primarily in the following aspects. First, this is the first study to examine how the designs of online review systems affect customers' review writing behaviors. In particular, we are the first to examine the direct and spillover effects of the closed-form evaluation of an attribute on the open-ended comments of the same attributes and other attributes. Second, this is the first study to analyze the role of review system design in how customers reveal their satisfaction through their reviews. That is, we are the first to examine and compare closed and open forms of reviews of various product or service attributes in reflecting customer overall satisfaction by analyzing the heterogeneity effect. Third, we discuss the role of providers' categorization as chain or independent in affecting the ambiguity of information and the direct, spillover, and heterogeneity effects. Thus, our findings in this study will help companies optimize their review system designs and better understand customers' online review behaviors and reflected perceptions. This will make it more efficient for managers to extract key information from substantial online customer reviews so that they can better use the generated eWOM effect.

2. Theoretical background and literature review

2.1. Theoretical background

The theoretical foundations of this study mainly lie in two theories related to information processing and customer satisfaction: the theory of information diagnosticity and ambiguity [24] and three-factor theory [48]. The theory of information diagnosticity and ambiguity [24] explains customers' online review writing and referral behaviors, whereas three-factor theory examines the different roles of various product or service attributes in affecting customers' positive or negative perceptions [48].

The theory of information diagnostics and ambiguity explains that various kinds of information include different levels of ambiguity that affect customer perceptions and their efforts to deal with that information [49,67]. Individuals tend to implement more intensive efforts—including describing, searching, and referencing information—when dealing with higher-ambiguity information, and their perceptions are influenced by more factors if the information has a higher level of ambiguity [38]. The ambiguity of information derives from two sources: content and form. In terms of content, information can be categorized as search-attribute related or experience-attribute related. Search attributes are attributes that are measurable and comparable so that customers can understand their performance by searching for that information. Conversely, experience attributes are attributes that can be evaluated only after consumption [74]. Therefore, experience attribute information is more ambiguous than search information. The content influences the quality of the information, which affects customer perception [16]. In terms of form, the way individuals describe the information affects its level of ambiguity.

The theory of information diagnosticity and ambiguity [24] frames the theoretical foundation of this study regarding customers' online review writing behaviors. Customers write online reviews to deliver information, and they strive to share high-quality information with a low level of ambiguity to help other customers [56]. Thus, they express different review behaviors when providing closed-form evaluations by voting for options such as "liked or disliked" or "pros or cons" from when writing open-ended textual comments. In this study, we claim these two review behaviors have a relationship, namely, direct and spillover effects. The direct effect focuses on how customers' closed-form evaluations of one product or service attribute affect their open-ended comments about the same attribute. Textual descriptions in an open form may contain more information, which helps alleviate information ambiguity [9]. However, the open-form evaluation that includes a substantial number of words can cause information overload [27]. Thus, the positive closed-form evaluation leads customers to comment less on the same attribute in their open-ended comments. However, the closed-form evaluation is a quantitative form of evaluation that limits the amount of information customers can describe. Thus, when customers express negative-form evaluations of a product or service attribute, they tend to use more detailed descriptions to elaborate on the reasons for their negative evaluation of that attribute and make the information less ambiguous and their reviews more persuasive. For the spillover effect, the closed-form evaluation, as a direct way to provide information for customers to make referrals, shows customers' positive or negative attitudes toward the particular product or service attributes [33]. The positive or negative attitudes toward these attributes affect customers' emotions when they write online reviews, which triggers customers to comment more on other attributes in their reviews to enrich the contents of their reviews and avoid information ambiguity.

Customers' comments reflect their perceptions of their consumption experience. Based on three-factor theory, the influence of various attributes on customer overall satisfaction is different [48]. This difference lies in two aspects: direction [1] and extent [2]. Regarding direction, depending on the role of various product or service attributes in affecting customer perception, those attributes can be categorized into excitement, basic, and performance factors. The high delivery of excitement factors arouses customer satisfaction, but their low delivery does not trigger customer dissatisfaction. Basic factors are necessary factors, which means their high delivery is assumed and does not arouse customer satisfaction, even though their low performance does arouse customer dissatisfaction. Performance factors have a bidirectional influence on customer satisfaction. When the performance of a performance factor is high, it leads to higher customer satisfaction, but the low performance of these factors causes higher dissatisfaction [1,48]. Regarding extent, the three-factory theory suggests that the influence of various product or service attributes on customers' overall satisfaction is asymmetric [2]. This is supported by the ring model [12] that asserts that core attributes have a higher impact on customers' overall satisfaction than auxiliary attributes. In online reviews, although both closed-form evaluations and open-ended comments show customer satisfaction, their mechanisms can be different. The mechanism is affected by the information delivery form – either the closed-form evaluations or open-ended comments, the property of providers (e.g., chain versus independent hotels in this study), and the different product or service attributes, as categorized by the excitement, basic, and performance factors, according to three-factor theory. This shows the heterogeneity effect of closed-form evaluations or open-ended comments in reflecting customers' overall satisfaction.

2.2. Online customer reviews

Online customer reviews have been intensively discussed in previous studies (e.g., [76,84]). These studies and discussions can be categorized into two types, depending on whether they focus on the language style or the contents of the reviews. Language characteristics include diversity, length, readability, sentiment polarity, and the subjectivity of the reviews [84]. Previous studies about the contents of online review have explored which aspects customers comment on in their textual reviews and how they reflect customer satisfaction (e.g., [4,76]). For example, Xiang et al. [76] summarized the frequency of the various attributes that are mentioned in online customer reviews and argued that the aspects mentioned most frequently indicate the customers' highest valuation. Berezina et al. [4] used text-link analytics to investigate how customer perceptions are linked with various attributes, particularly their satisfaction and dissatisfaction.

Although reviews can reflect customer satisfaction, the purpose of writing reviews is not limited to reporting satisfaction. Customers' review writing process is complex mainly because of three reasons. First, as three-factor theory has elaborated, the ways customers show their perceptions through their evaluations of various product or service attributes can be different depending on the role of the attributes in affecting customer perception [48].

The second reason for the complexity of customers' online review behaviors is that the purposes of writing reviews are diverse. In addition to revealing satisfaction, the purposes of writing reviews include providing information altruistically to other participants in the online community in the form of references, releasing customers' emotions, seeking economic compensation, and meeting customers' psychological needs to socially interact with participants [18,28]. In particular, seeking votes for being helpful is one of the motivations for customers to interact with online participants to satisfy their social needs. Previous studies have examined the determinants of the helpfulness of online reviews, which include semantic characteristics, namely, the meaning of the words in the review [6]; persuasiveness [83]; and the writing style, sentiment, timeliness [43], and contents of reviews [3].

The third reason for the complexity of customers' online review behaviors is that the forms of customer reviews are diverse. Previous studies about online customer reviews have focused on customer ratings (e.g., [33]) or textual comments (e.g., [4]). With the development of the platform economy, even more diverse review systems have emerged, and they can trigger different review behaviors. Previous studies (e.g., [72]) found that the format of the questions may affect individuals' responses. However, the role of the design of review systems in affecting customers' overall satisfaction reflected in online reviews has not been discussed in the previous literature.

In this study, we focus on both online customer review behavior and reflected customer satisfaction and examine how they are affected by the forms of review options—the closed form evaluations or the open structure of textual comments. Thus, we contribute to the field of online customer reviews by examining the role of review system design in affecting customers' online review writing behaviors.

3. Hypothesis development

3.1. Direct effect of closed-form evaluation of attributes on open-ended comments of the corresponding attributes

Positive closed-form evaluations serve as a direct way to commend providers for their high performance [57]. Customers typically maintain relatively clear criteria for the high qualities of product and service attributes, and their expectations are relatively consistent [26]. Thus, a positive closed-form evaluation of attributes shows a positive attitude, which reduces customers' behavior regarding commenting on the details of these attributes, thus preventing information overload [71]. It can also save hassle costs and avoid the repetition of revealing customers' positive attitude. Based on the above discussion, we propose the following hypothesis:

H1a. : A positive closed-form evaluation of attributes leads customers to comment less on the same attribute in open-ended comments.

When customers are dissatisfied with certain attributes, they are likely to vote them as "cons" or as "disliked" in negative closed-form evaluations. Many customers view their online reviews as cognitive evaluations of providers rather than as simple expressions of their own emotions [29]. Many customers seek acknowledgement of their reviews from other readers in the online community, as measured by the level of helpfulness [63]. Thus, customers attempt to make their evaluations persuasive by detailing the disadvantages of certain attributes and the reasons for their low satisfaction [10]. In this way, they can warn future customers by showing detailed evidence of what led to their negative conclusions [37]. Therefore, based on the preceding discussion, we hypothesize:

H1b. : A negative closed-form evaluation of attributes triggers customers to comment more on the same attribute in open-ended comments.

Customers incur costs when writing online reviews. These costs include both monetary costs, such as the costs associated with using the internet and electronic devices, and hassle costs, such as time and effort [14]. Hassle costs are typically greater than the monetary costs of online review writing and posting. Customers who are dissatisfied with the providers or their products are strongly motivated to reveal their negative perceptions and emotions in complaints [37]. Online customer reviews are an effective forum for complaints because of their anonymity and the fact that contact with the providers is indirect, so customers do not have to worry about "losing face" when interacting online [31]. Further, writing online reviews costs less than making formal complaints to regulating agents. Customers are strongly motivated to persuade other participants in the online community by detailing evidence showing the objectivity of their ratings [84]. Moreover, a detailed comment about an attribute they rate negatively is an efficient way for customers to urge providers to improve their corresponding performance [66]. Comparatively, when rating certain attributes as positive, customers still may want to provide supplementary comments related to those attributes to strengthen their praise of the providers and show their satisfaction with the attributes [58]. Therefore, relatively speaking, customers have more incentive to complain about the disadvantages of the attributes than they have to objectively organize their positive comments [13]. Based on the above discussion, we hypothesize the asymmetric effect:

H1c. : The role of negative closed-form evaluations of attributes in increasing customers' behaviors regarding writing details about the same attributes in open-ended comments is more significant than the role of positive closed-form evaluations of attributes in reducing open-ended comments about those attributes.

3.2. The spillover effect of closed-form evaluations of certain attributes on open-ended comments about other attributes

Customers have various ways of providing information, including through closed and open forms. Compared with the open form, the closed form is a more direct way of conducting evaluations and showing customer perceptions, whether they are extremely positive or negative [59]. Customers' overall perceptions of the consumption experience are affected by the integration of various product or service performances [32]. Thus, their extreme positive or negative evaluations of certain attributes trigger customers' positive or negative emotions regarding the entire consumption experience, which urges them to comment on other attributes to write a comprehensive review [21].

Additionally, according to the theory of information diagnosticity and ambiguity [24], individuals try to avoid information ambiguity. One of the motivations for customers to write and post online reviews is altruism, where they provide information about their consumption experience to future customers in the form of referrals [84]. This shows the important functions of online reviews in reducing the perceived risks for future customers, who become more familiar with the providers through existing reviews [30]. Thus, when customers provide their evaluations of certain attributes through the closed form to show their attitudes, they also tend to show their attitudes toward other attributes by providing information through open-ended comments to earn votes for helpfulness and to interact socially with other participants in the online community [83]. Further, the hassle cost of evaluating attributes in the closed form is lower than that of writing open-ended comments, so the choice of advantages or disadvantages sometimes results in a biased impression of customer perception [64]. This also leads to the effect of the trigger mechanism of the closed-form evaluation of an attribute on open-ended comments on other attributes. Therefore, based on the above discussion, we hypothesize:

H2. : The closed-form evaluation of an attribute causes customers to comment more on other attributes in open-ended comments.

3.3. The heterogeneity effect of closed-form evaluation and open-form comments of attributes on customers' overall satisfaction

In a closed-form evaluation, customers can vote either positively or negatively, or they can refrain from voting, indicating that their perception is neutral. A positive vote for certain attributes indicates customers are satisfied with those attributes. Positive closed-form evaluations of attributes show customers' positive attitudes toward these attributes, which can have a positive effect on their overall satisfaction. However, that effect is diminished for the following two reasons. First, according to three-factor theory [48], positive attitudes toward basic factors do not lead to overall satisfaction. With the increasing expectations of customers regarding providers' products and services, many factors are becoming requisite factors [15]; thus, a positive evaluation in a closed-form review does not reflect overall satisfaction. Second, the design of the closed-form evaluation does not differentiate customers' levels of positive attitudes toward the attributes. That is, customers vote for those attributes irrespective of whether they are extremely satisfied or generally satisfied.

Customers must put time and effort into writing their textual comments, raising their hassle costs. More detailed comments require more work and higher associated hassle costs, which demonstrates that high satisfaction can outweigh the cost of time and effort [81]. Further, when the comments are more detailed, this shows that customers want to commend the providers and reveal their higher overall satisfaction [4]. Therefore, based on the above discussion, we propose the following hypothesis:

H3a. : Regarding the advantages of attributes, open-ended comments about attributes have a more significant effect than closed-form evaluations of the same attributes in reflecting overall customer satisfaction.

Regarding the disadvantages of attributes, customers can use a closed-form evaluation to directly show their negative attitudes. According to three-factor theory, for both basic and performance factors, attribute-level low performance of these attributes negatively affects their overall satisfaction [51]. However, when customers use more detail in open-ended comments to show their negative attitudes toward that attribute, some noise remains in reflecting their overall satisfaction in their negative comments. First, customers tend to reveal their negative emotions through their complaints in their reviews [39]. Therefore, longer negative reviews can reveal extreme negative emotions rather than objective evaluations of the consumption experience. Second, one of the motivations for customers to write negative comments is to warn future customers; thus, the details that describe the disadvantages of the attributes can make the argument more persuasive by providing more evidence [65]. Third, customers tend to urge providers to make improvements by detailing their consumption experience [66]. The above reasons make the reflection of negative textual comments on customer overall satisfaction less significant than the reflection of closed-form evaluations. Thus, based on the preceding discussion, we hypothesize:

H3b. : Regarding the disadvantages of attributes, closed-form evaluations of attributes have a more significant effect than open-ended comments on the same attributes in reflecting overall customer satisfaction.

3.4. Comparison of direct, spillover, and heterogeneity effect for chain versus independent hotels

The theory of information diagnosticity and ambiguity [24] argues that individuals try to alleviate ambiguity by gathering more information. Compared with chain providers, independent providers employ more varied standards and operations procedures, and many of those have unique features [79]. Customers, therefore, may have less clear expectations of independent providers, and they may be more excited when the providers achieve a high performance on certain attributes [46]. This encourages them to use closed-form positive evaluations (e.g., voting for “liked”, recommending, or thumbing up) rather than the open comments to show their favor of certain attributes directly and commend and support the providers. However, when they encounter a negative performance from independent providers, customers feel an urge to comment in more detail about their negative attitudes and complain by casting a negative vote in their closed-form evaluations [66]. Thus, we hypothesize:

H4a. : The direct effect of the closed-form evaluation of attributes in influencing customers to comment about the same attributes in open-ended comments is more significant for independent providers than for chain providers.

Compared with the brand effect of chain providers, customers have less familiarity with independent providers [45]. This, in turn, motivates customers to evaluate and provide more details about the advantages and disadvantages of the product or service attributes from independent providers to alleviate ambiguity for future customers. This also shows the altruism of online reviews that feature comprehensive descriptions and evaluations of most product or service attributes [10]. For independent providers, because of their more varied operations, customers may have less clear expectations and may be more sensitive to the performance of various attributes than for chain providers [55]. Thus, their attitudes toward one attribute may trigger a reaction that makes them pay attention and comment on other attributes in the open-ended comments. Therefore, based on the above discussion, we propose the following hypothesis:

H4b. : The spillover effect of the closed-form evaluation of attributes in influencing customers to comment about the same attributes in open-ended comments is more significant for independent providers than for chain providers.

Because of the more varied operations and standards of independent providers, customers tend to use more diverse descriptions and comment differently in the reviews of independent providers compared with their reviews of chain providers, which are more consistent. These varied evaluations are motivated by diverse factors such as altruism and the need to interact socially with other participants in online communities [84]. This reduces the reflection of online reviews on customer satisfaction [76], and thus amplifies the heterogeneity effect between closed-form evaluations and open-ended comments of attributes on reflecting customers’ overall satisfaction. Therefore, we hypothesize:

H4c. : The heterogeneity effect between closed-form evaluations of attributes and open-ended comments about those attributes in reflecting customer overall satisfaction is more significant for independent providers than for chain providers.

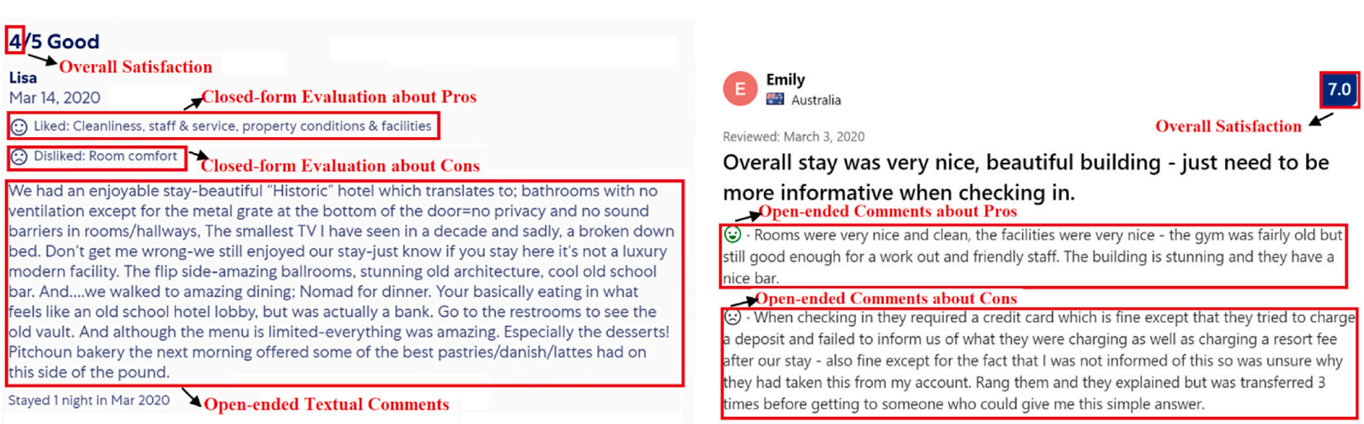
4. Data analytics

4.1. Data collection

We collected data from two popular travel websites, Expedia.com and Booking.com, which have been discussed in previous studies (e.g., [22,47]). We collected data during a one-year study period from March 16, 2019, to March 15, 2020. Expedia.com provides customers with review opportunities through both closed-form evaluations (likes or dislikes) and open-ended text comments, as shown in Fig. 1(a). We used the data from Expedia to test hypotheses 1 and 2 about the relationship between closed-form evaluations and open-ended text comments and to analyze the direct and spillover effects. Booking.com provides opportunities for customers to write and post positive and negative comments separately, as depicted in Fig. 1(b). Both Expedia.com and Booking.com ask customers about their overall satisfaction, as shown by overall ratings. To ensure the reviews we collected from the two platforms were from the same hotels, we first filtered the hotels listed on both websites. Then, based on a sampling method from previous studies (e.g., [76]), we collected online customer reviews from 1200 hotels located in the 100 largest U.S. cities based on the U.S. Census Bureau’s population estimates. For each city, we grouped the hotels into two categories: chain and independent. We then generated six random numbers as indices from one to the number of hotels in that group to collect online customer reviews from six chain hotels and six independent hotels from Expedia.com. We paired the same hotels to collect the samples from Booking.com to ensure that the hotels were the same. Then, for each hotel, we generated 10 random numbers from one to the total number of reviews in our one-year study period as indices for that hotel, and we collected reviews with those indices. Reviews were dropped if data such as textual comments were missing. Then, we regenerated the random numbers to repeat the process until the required number of reviews was acquired. The final data set for the analysis of results included 12,000 reviews. Half that number—6000 reviews—came from 600 chain hotels, and the other half came from 600 independent hotels.

4.2. Feature engineering

Online customer reviews contain rich data that provide a great opportunity for companies to understand customers’ consumption experience. However, the substantial number of reviews and their open structure cause managers to experience information overload.



(a) *Expedia.com* (b) *Booking.com*

Fig. 1. Online review system on Expedia.com and Booking.com

Traditional methods of analyzing text data, such as content analysis, may not be efficient or even feasible with such substantial and unconstructed reviews. Referring to previous studies (e.g., [36,77]: [78]), we used latent semantic analysis (LSA) as a text mining approach to examine online customer reviews. LSA is well suited to analyzing human natural languages by extracting the hidden semantic structures from words, phrases, and sentences [36]. As an approach to topic modeling, the mathematical essence of LSA lies in dimension reduction through factor clustering [77].

Based on previous studies (e.g., [36]), we conducted LSA in three steps using RapidMiner software. For the first step—preprocessing the textual data—we transferred all letters into lowercase and then removed all trivial words, including tokens such as "a" and "an" with two letters or fewer. We then removed all words such as "are" and "the" that had no actual meaning. Additionally, we removed all words that appeared only once. As a result, we avoided increasing the term frequency matrix unnecessarily. After that, we used term-stemming techniques to identify words with the same roots. For example, the words "exciting," "excited," and "excitement" all have the same root and were considered one token. Last, we conducted an *n*-gram algorithm by setting n equal to 3 to identify repeated phrases containing three or fewer words. For example, using that method, phrases such as "excellent staff," "comfortable room," and "old facility" were identified.

For the second step, we used the term frequency–inverse document frequency weighting method to conduct the term frequency matrix transformation [41]. As a result, we could discount common terms but assign more weight to rare terms. That step ensured that the uniqueness, instead of the commonality, of each document could be identified. In detail, in the transformed term-frequency matrix, the weights w_{ij} were determined by the product of the term frequency tf_{ij} and the frequency of token i appearing in the document, namely, idf_i. That is, $w_{ij} = tf_{ij} \times idf_i$. The variable of$idf_i$ was determined by the number of documents in total divided by the frequency of documents having token i. That is, $idf_i = log(N/df_i)$.

The third step was singular value decomposition (SVD). Referring to previous research (e.g., [25,50]), we calculated the SVD matrix $X_{ab} = A_{aa}B_{ab}C_{bb}^T$, in which A, B, and C were all matrices. Matrix A contained columns with the orthonormal eigenvectors of VV^T. Matrix B had the square root form of the eigenvalues of matrix A or C. Matrix C had columns with the orthonormal eigenvectorsV^TV. In the SVD process, we considered matrix A as an $h \times m$ matrix. That is, it had an m-dimensional space in which h points lay. Then, the objective was to find the optimal k-dimensional subspace to fit in this set of points by minimizing the distance in their squares of the perpendicular form to the subspace. Following the approaches of previous studies (e.g., [25]), we used the best least squares fit algorithms. First, we figured out the optimal fitting line through the origin to begin with a one-dimensional subspace. Then, we extended this to more dimensions with a set of points $\{x_i | 1 \leq i \leq m\}$ to apply this optimal fit algorithm.

Table 1 presents the results of the latent textual factors mined from the online customer reviews from Expedia through LSA. Other latent textual factors, such as location and value, were mined using LSA; however, because the closed-form evaluations of those attributes were not available on Expedia.com, we did not present those latent textual factors in Table 1, and neither were they used for text regressions. In Table 1, for demonstration purposes, we listed the top ten terms for each textual factor as the high-loading terms.

Table 2 presents the results of the latent textual factors mined using LSA from the positive and negative comments, respectively, taken from online customer reviews on Booking.com. To be consistent with the aforementioned presentation, we did not list any extra latent textual factors mined using LSA, such as location and value, which were not used in the text regressions.

4.3. Text regression

After conducting LSA, we conducted text regression based on the procedures used in previous studies (e.g., [53,54]). To analyze customer review behavior, we examined the textual vector space of each online review of each attribute mined using LSA; these were the latent textual factors. *Cleanliness* was not an independent latent textual factor mined from LSA; rather, it was an important element in the latent factor of *maintenance and operations*. Therefore, we used the space vector of the online reviews on this latent factor to make a proxy. The space vector of an online review was measured by the f-dimensional coordinates of the review on the f-dimensional space. Table 3 visually shows the coordinates of the reviews on each latent textual factor, in which the element $x_{ip}(1 \leq i \leq r, 1 \leq p \leq f)$ represents the coordinate value of review i on the latent textual factor r, namely, the loading of review i on the attribute r. We had $f \times r$ coordinates in total, where $f$represented the number of latent factors (attributes) mined from LSA, and r represented the total number of reviews. The coordinates of the textual vectors had important meanings [36]. Technically, when the coordinate of the textual vector had a higher value, this implied that the corresponding review had a higher loading on that latent factor. Practically, when the coordinate had a higher value, this showed that the online reviews had more relevance for that product or service attribute. That is, in an online review, the customer focuses more on a certain attribute by providing more detailed descriptions or evaluations of that attribute.

The text regression model used in this study is listed in Eq. (1).

$$Coordinate\_attribute_i = \beta_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_3X_4 + \varepsilon_i \tag{1}$$

where i represents the review i. To test the direct and indirect effect, the dependent variable is the coordinate of each review i on a corresponding

Table 1
Corresponding textual factors of online customer reviews from Expedia.com.

Interpretations (labels) of factors	High-loading terms
Room	room, bathroom, toilet, bed, pillow, queen_bed, bathtub, bed_soft, room_spacious, king_bed
Staff and Service	front_desk, ladi, maid, staff, employee, response, service, behave, housekeep, attitude
Amenities	coffee_maker, tv, ice_machine, microwave, fridge, board, portal, cup, dryer, phone
Facilities	business_center, gym, pool, center, elevator, décor, lobbi, hallwai, garden, swim_pool
Maintenance and Operations	maintain, clean, noise, check, parking, load, wait, sweep, securiti, patrol

Table 2
Corresponding textual factors of online customer reviews from Booking.com.

Interpretations (labels) of factors	High-loading terms for positive comments	High-loading terms for negative comments
Room	room, spacious, bed, queen_bed, comfort, sleep, king_bed, large_room, room_comfort, guest_room	room_bed, room, soft_bed, bathtub, bathroom, toilet, queen_bed, room_stay, king_bed, room_window
Staff and Service	ladi, people, staff, service, friendli_staff, polite, nice_staff, employee, excellent_service, maid	front_desk_slow, slow_response, staff, rude, housekeep, attitude, waiter, behave, service, employee
Amenities	tv, audio, coffee_machine, fridg, microwave, ice_machine, brochure, picture, map, screen	ice_maker, cup, board, dryer, towel, fridg, water_cup, internet, paper, curtain
Facilities	printer_boarding_pass, auto_machine, gym, pool_area, business_center, décor, fit_center, café, lobbi, center	elevator_slow, hallwai, stair, lobbi_crowd, gym, center, wall, pool, business_center, carpet
Maintenance and Operations	shuttle, gate_open, free_shuttle, maintain, valet, clean, safe, check_frequent, sweep, keep	wait, noise, parking, space, smoke, dirt, smell, loud, wait_time, smell_bad

Table 3
Matrix of coordinates of each review.

	f Latent Factors Mined From LSA						
Review #	Factor 1	Factor 2	Factor 3	…	Factor *p*	…	Factor *f*
Review 1	x_{11}	x_{12}	x_{13}	…	x_{1p}	…	x_{1f}
Review 2	x_{21}	x_{22}	x_{23}	…	x_{2p}	…	x_{2f}
Review 3	x_{31}	x_{32}	x_{33}	…	x_{3p}	…	x_{3f}
…	…	…	…	…	…	…	…
Review *i*	x_{i1}	x_{i2}	x_{i3}	…	x_{ip}	…	x_{if}
…	…	…	…	…	…	…	…
Review *r*	x_{r1}	r_{n2}	r_{n3}	…	r_{np}	…	r_{nf}

attribute (i.e., room, staff and service, amenities, facilities, and maintenance and operations). Referring to previous studies (e.g., [5,62]), we classified the independent variables into four categories. The first two categories were content-based positive or negative cues, respectively; the third category was linguistic-based cues; and the fourth category was the control variable. The first category of variables was the positive closed-form evaluations of the attributes. Namely, the variable (*Pos_ame*, *Pos_ops*, *Pos_fac*, *Pos_rm*, *Pos_staff*) was coded as 1 if customers voted that they "liked" that attribute; otherwise, it was coded a 0. That is, the vector X_1 is in the form of $[x_{11}, x_{12}, \ldots, x_{15}]$representing the five positive closed-form evaluations of the attributes. Similarly, the second category of variables was the negative closed-form evaluations of the attributes. That is, the variable (*neg_ame*, *neg_ops*, *neg_fac*, *neg_rm*, *neg_staff*) was coded as 1 if customers voted that they "disliked" that attribute; otherwise, it was coded as 0. Namely, the vector X_2 is in the form of $[x_{21}, x_{22}, \ldots, x_{25}]$ representing the five negative closed-form evaluations of attributes. The third category of variables referred to linguistic cues. Referring to previous studies (e.g., [60]), we include two of the most important linguistic characteristics of reviews in the vector X_3, which is in the form of $[x_{31}, x_{32}]$—namely, the online reviews' sentiment polarity (denoted as *Sentiment*; [60]) reflecting the construct of affect (i.e., emotion) and the length of reviews (denoted as *Length*; [23]) reflecting the complexity of the online reviews. In detail, sentiment polarity was obtained by sentiment analysis through coding in SentiStrength software [68,70]. The value of sentiment polarity ranged from −4 to 4, with higher numbers meaning more positive emotions. A positive or negative sentiment polarity showed customers revealing positive and negative emotions, respectively, in their online reviews. If the sentiment polarity had a value of 0, this means customers had neutral emotions when writing their reviews. Referring to previous studies (e.g., [40]), we measured the length of reviews by the number of words. As the length of the reviews increased, so did the level of linguistic complexity [62]. Last, referring to previous studies (e.g., [7,34]), to control the length of time that customers were served by providers, where a longer length of time indicated a more intensive buyer-supplier relationship, we added the number of nights the customers stayed X_4 (denoted as *Nights*) as the control variable, which was the value collected from each online customer review from Expedia.com. To test the heterogeneity effect, the dependent variable was customers' overall ratings of their satisfaction. The independent variables for the content and linguistic-based cues were the same for Expedia reviews for the closed-form evaluations. However, for open-ended comments on Booking.com, content-based cues were the coordinates of each review on each latent textual factor in positive or negative comments. A brief description of the variables and their descriptive statistics is provided in Table 4. The procedure of the data analytics is visually described in Fig. 2.

We presented the correlation of the variables in Table 5. We also checked the VIF values for each of these variables, which were in the range of 1.169 to 2.457, and were therefore below the threshold of 3. This indicated that multicollinearity was not an issue [20,35].

Tables 6 and 7 present the results of text regressions to test H1 and H2 to show the direct and spillover effects of closed-form evaluations of various attributes on open-ended comments about corresponding and other attributes for chain and independent hotels, respectively. The econometric model to test the direct and spillover effect is presented in Eq. (2).

$$
\begin{aligned}
Attribute\_coordinate_i = {} & \beta_0 + \beta_1 pos\_ame_i + \beta_2 pos\_ops_i + \beta_3 pos\_fac_i + \beta_4 pos\_rm_i + \beta_5 pos\_staff_i + \beta_6 neg\_ame_i \\
& + \beta_7 neg\_ops_i + \beta_8 neg\_fac_i + \beta_9 neg\_rm_i + \beta_{10} neg\_staff_i + \beta_{11} sentiment_i + \beta_{12} length_i + \beta_{13} nights_i + \varepsilon_i
\end{aligned}
\tag{2}
$$

where *i* represents online review *i*. The dependent variable is the coordinate of reviews of the attributes of amenities, operations, facilities,

Table 4
Description and descriptive statistics of variables.

Variables	Description	Type	Mean	Std	Min	Max
Pos_attribute (open form)	Coordinate values of positive comments on latent factors mined from LSA	Numeric	0.02	0.04	0.00	0.30
Neg_attribute (open form)	Coordinate values of negative comments on latent factors mined from LSA	Numeric	0.02	0.04	0.00	0.31
Pos_attribute (closed form)	Whether customers voted "Liked," showing their positive attitudes toward attributes, which included amenities (*Pos_ame*), cleanliness (*Pos_ops*), facilities (*Pos_fac*), room comfort (*Pos_rm*), and staff and services (*Pos_staff*)	Dummy	0.22	0.42	0.00	1.00
Neg_attribute (closed form)	Whether customers voted "Disliked," showing their negative attitudes toward attributes, which included amenities (*neg_ame*), cleanliness (*neg_ops*), facilities (*neg_fac*), room comfort (*neg_rm*), and staff and services (*neg_staff*)	Dummy	0.21	0.41	0.00	1.00
Rating (Expedia)	Customer ratings posted on their online reviews on Expedia.com showing their overall satisfaction	Numeric	3.77	1.46	1.00	5.00
Rating (Booking.com)	Customer ratings posted on their online reviews on Expedia.com showing their overall satisfaction	Numeric	8.06	2.32	1.00	10.00
Review Length (Expedia)	Number of words in online customer reviews on Expedia	Numeric	36.26	29.22	3.00	120.00
Review Length (Booking.com)	Number of words in online customer reviews on Booking.com	Numeric	36.37	45.29	6.00	189.00
Sentiment (Expedia)	Sentiment polarity of online customer reviews on Expedia; a higher value showed a more positive emotion	Numeric	0.13	2.33	−4.00	4.00
Sentiment (Booking.com)	Sentiment polarity of online customer reviews on Booking.com; a higher value showed a more positive emotion	Numeric	0.98	2.24	−4.00	4.00
Nights	Number of nights customers stayed in hotel	Numeric	1.63	1.26	1.00	6.00

room, and staff, respectively, in each of the columns in Tables 6 and 7. The independent variables include the positive or negative closed-form evaluations of amenities, maintenance and operations, facilities, room, and staff and services, along with the sentiment of reviews, length of reviews, and number of nights a customer stayed in a hotel. As elaborated above, the positive closed-form evaluations of the above attributes were in the dummy form, depending on whether customers voted "liked." Similarly, the negative closed-form evaluations of the above attributes were also in the dummy form, depending on whether customers voted "disliked." For a certain attribute, it is quite possible that customers did not either vote "liked" or "disliked," indicating their relatively neutral attitudes toward that attribute. The standardized coefficients are reported. To better illustrate the direct effect versus the spillover effect, we present the direct effect coefficients in Column 1, separately from the direct effects in Columns 2–6 in Table 6 and Table 7.

Next, we analyzed H3, the heterogeneity effect of the closed-form evaluations and open-ended comments of various attributes on the reflection of customers' overall satisfaction, using data from Expedia.com and Booking.com, respectively. The econometric model is in Eq. (3), with the results in Table 8.

$$
\begin{aligned}
Overall\_rating_i = {} & \beta_0 + \beta_1 pos\_ame_i + \beta_2 pos\_ops_i + \beta_3 pos\_fac_i + \beta_4 pos\_rm_i + \beta_5 pos\_staff_i + \beta_6 neg\_ame_i + \beta_7 neg\_ops_i \\
& + \beta_8 neg\_fac_i + \beta_9 neg\_rm_i + \beta_{10} neg\_staff_i + \beta_{10} neg\_staff_i + \beta_{11} sentiment_i + \beta_{12} length_i + \beta_{13} nights_i + \varepsilon_i
\end{aligned} \tag{3}
$$

where i represents online review i. The dependent variable is the rating customers posted in their online reviews to measure customer overall satisfaction [44]. The independent variables include closed-form evaluations or open-ended comments of amenities, maintenance and operations, facilities, room, and staff and services on Expedia and Booking.com, respectively. The independent variables also include the sentiment of reviews and the length of reviews. Because information on the number of nights is not available on Booking.com, we did not include it in the open-ended comments models, but only in the closed-form evaluations models. The standardized coefficients were reported. Referring to previous studies (e.g., [11,69]), in Tables 6, 7, and 8, we present the results of chain and independent hotels separately.

5. Discussion

5.1. Direct effect

The direct effect examines the impact of closed-form evaluations of a product or service attribute on customers' review behavior regarding the same attribute, and the results for H1 answer the first research question. Our findings from Tables 6 and 7 partially support H1a. For example, in Table 6 about chain hotels, we find that most of the closed-form positive evaluations of attributes, such as amenities ($\beta_1 = -0.29$, $p < 0.05$), facilities ($\beta_3 = -0.17, p < 0.1$), and room ($\beta_4 = -0.19, p < 0.05$), reduce customers' behaviors regarding writing details about the same attribute in open-ended comments. The positive evaluations of certain attributes already show customers' direct perceptions of those attributes; thus, customers tend to reduce their behaviors regarding writing in more detail and expand their descriptions. Additionally, we find that, for the attribute of cleanliness, the relationship between positive evaluation and the comments is insignificant. That is because cleanliness is part of providers' operations; however, operations and maintenance include many other aspects, such as security and noise control. Thus, the effect is insignificant.

Additionally, the results from Tables 6 and 7 fully support H1b. The negative closed-form evaluations of attributes increase customers' behaviors regarding writing details in open-ended comments about those attributes, including amenities ($\beta_6 = 0.69$, $p < 0.01$), operations ($\beta_7 = 0.39$, $p < 0.05$), facilities ($\beta_8 = 0.22$, $p < 0.05$), room ($\beta_9 = 0.26$, $p < 0.01$), and staff and service ($\beta_{10} = 0.25$, $p < 0.01$) in Table 6. When customers rate the attributes negatively, they tend to use more text to explain the reasons for their negative evaluation, to describe their bad consumption experiences, and to make complaints. Customers use those details in the textual comments to make their evaluations more persuasive [80]. These findings support the theory of information diagnosticity and ambiguity [24], which asserts that customers strive to avoid or alleviate information ambiguity by providing more detailed reasoning about their negative closed-form evaluations in their textual comments.

Further, when comparing the standardized coefficients for positive and negative effects, we find that, for all attributes, the negative closed-form evaluations of attributes have a greater effect on increasing customers' behaviors regarding writing details about the same attributes in open-ended comments than positive closed-form evaluations of attributes on reducing open-ended comments about those attributes. This finding fully supports H1c. This asymmetric effect shows that customers have more incentive to reveal their negative perceptions by criticizing unsatisfactory attributes than they do by commending positive attributes.

5.2. Spillover effect

The spillover effect refers to the impact of the closed-form evaluations of a product or service attribute on customers' review behaviors of the other attributes, and the results of H2 answer the second research question. The results from Tables 6 and 7 suggest that, for some of the attributes, closed-form evaluations increase customers' incentives to write in detail about other attributes in the open-ended comments. This finding partially supports H2 for the spillover effects. For example, from Table 6, we can find that customers write more about amenities in their textual comments when they have made negative closed-form evaluations of facilities ($\beta_8 = 0.31, p < 0.05$) and room ($\beta_9 = 0.33, p < 0.05$). As another example, customers write more about room in their textual comments when they have made positive closed-form evaluations of amenities ($\beta_1 = 0.16$, $p < 0.1$) and facilities ($\beta_3 = 0.19$, $p < 0.05$). The spillover effects links customers' closed-form evaluations of an attribute to their review behaviors regarding other attributes in their textual comments.

5.3. Heterogeneity effect

From Table 8, we can find the heterogeneity effect between closed-form evaluations and open-ended comments on the reflection of customers' overall satisfaction. This finding supports H3 and answers the third research question. In detail, regarding the advantages of the attributes, the open-ended comments about the attributes have a more significant effect than the closed-form evaluations of those attributes in affecting customers' overall satisfaction, supporting H3a. For closed-form evaluations, only the closed-form positive evaluations of room ($\beta_4 = 0.31$, $p < 0.01$) and staff and service ($\beta_5 = 0.26$, $p < 0.01$) significantly reflect positive overall customer satisfaction. However, for open-ended comments for both chain and independent hotels and for all attributes except operations, the higher relevance of the attributes in the positive comments significantly reflects higher overall satisfaction. This is because, compared with closed-form evaluations, customers incur more hassle costs to write online reviews. Thus, when positive

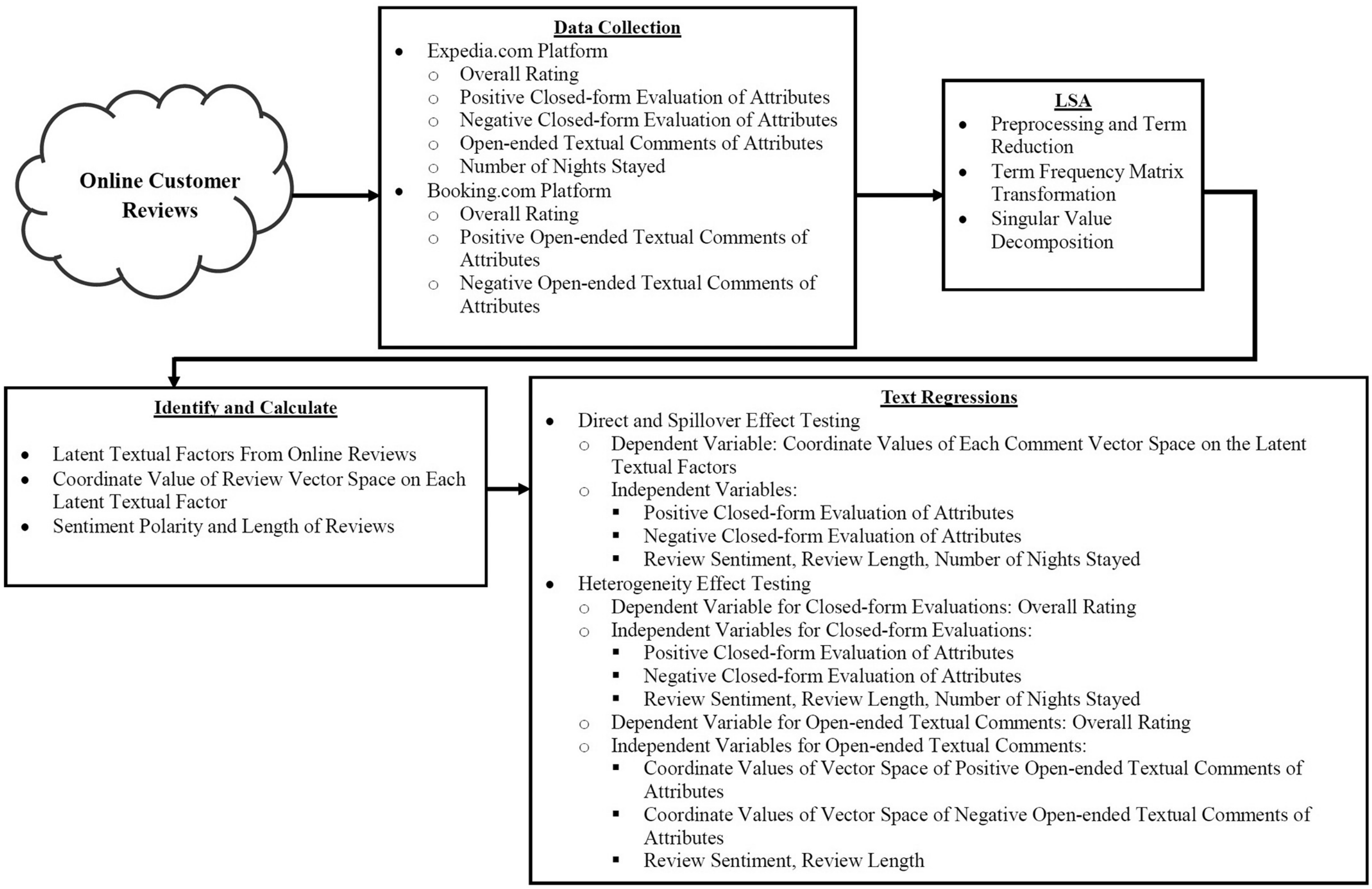


Fig. 2. Procedure of data analytics.

Table 5
Correlation matrix of variables.

	Pos_ame	*Pos_ops*	*Pos_fac*	*Pos_rm*	*Pos_staff*	*Neg_ame*	*Neg_ops*	*Neg_fac*	*Neg_rm*	*Neg_staff*	*Sentiment*	*Length*
Pos_ame	1.00											
Pos_ops	0.10	1.00										
Pos_fac	−0.22	0.04	1.00									
Pos_rm	−0.04	−0.02	0.12	1.00								
Pos_staff	0.22	0.04	−0.04	−0.28	1.00							
Neg_ame	−0.27	−0.07	0.08	0.02	0.26	1.00						
Neg_ops	−0.20	−0.29	0.00	0.18	0.00	−0.27	1.00					
Neg_fac	0.00	0.22	−0.25	−0.28	−0.25	−0.11	0.00	1.00				
Neg_rm	0.00	0.04	−0.04	−0.28	0.17	0.08	−0.22	−0.04	1.00			
Neg_staff	−0.22	0.04	0.17	−0.08	−0.25	−0.11	0.00	−0.04	−0.04	1.00		
Sentiment	0.10	0.01	0.12	0.28	0.26	−0.13	−0.29	−0.03	−0.10	−0.07	1.00	
Length	0.03	0.08	−0.11	−0.13	−0.14	0.12	0.14	−0.01	0.12	0.25	−0.21	1.00

comments about various product or service attributes are more detailed, this indicates that customers are willing to commend providers by making a bigger effort, reflecting their higher overall satisfaction with providers. Thus, positive open-ended comments, compared with closed-form evaluations, have a more significant positive reflection of customers' overall satisfaction.

However, regarding the disadvantages of the attributes, we find that negative textual comments contain more noise in their reflections of low customer satisfaction than negative closed-form evaluations. This finding supports H3b. As suggested by the results in Table 8, negative closed-form evaluations of most attributes, including amenities ($\beta_6 = -0.22, p < 0.05$), operations ($\beta_7 = -0.26, p < 0.01$), room ($\beta_9 = -0.20$, $p < 0.05$), and staff and service ($\beta_{10} = -0.21, p < 0.05$), significantly negatively affect overall customer satisfaction. Comparatively, the textual comments reveal more negative emotions through customers' complaints, blaming of providers, and warnings to other customers by providing more details [17]. Only for the attributes of room and staff and services does a greater focus on those attributes in the textual comments more significantly reflect customers' low overall satisfaction with chain and independent hotels. Thus, the negative closed-form evaluations contain a more significant negative reflection of customer overall satisfaction than do open-ended comments. The findings support three-factor theory [48] by categorizing the attributes based on their influence on customers' overall satisfaction. Additionally, we find the review structure affects the categorization.

5.4. Chain versus independent hotels

The results of H4 answer the fourth research question about the differences between chain and independent hotels regarding their

Table 6
Direct effects and spillover effects for chain hotels.

Closed-form Evaluations	Dependent variable (Coordinates of reviews on the corresponding attribute)					
	Direct effects	Spillover effects	Spillover effects	Spillover effects	Spillover effects	Spillover effects
	Corresponding attributes	Amenities	Maintenance & operations	Facilities	Room	Staff & services
Pos_ame (β_1)	−0.29**		0.20	0.02	0.16*	−0.03
Pos_ops (β_2)	−0.16	0.02		0.11	0.05	0.19**
Pos_fac (β_3)	−0.17*	−0.15	0.21		0.19**	−0.03
Pos_rm (β_4)	−0.19**	0.26*	0.23	0.27***		−0.07
Pos_staff (β_5)	−0.12	0.12	0.65***	0.13	0.11	
neg_ame (β_6)	0.69***		0.19	0.10	0.16*	0.13
neg_ops (β_7)	0.39**	−0.04		−0.05	0.13	0.18**
neg_fac (β_8)	0.22**	0.31**	0.18		0.18**	−0.09
neg_rm (β_9)	0.26***	0.33**	0.02	0.16*		0.07
neg_staff (β_{10})	0.25***	0.08	0.38**	0.07	0.10	
Sentiment (β_{11})		−0.07	−0.35*	0.05	0.20**	0.20**
Length (β_{12})		−0.01	−0.39**	−0.04	0.18**	0.16*
Nights (β_{13})		0.37***	−0.07	0.15*	0.19**	0.18**

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7
Direct effects and spillover effects for independent hotels.

Closed-form evaluations	Dependent variable (Coordinates of reviews on the corresponding attribute)					
	Direct effects	Spillover effects	Spillover effects	Spillover effects	Spillover effects	Spillover effects
	Corresponding attributes	Amenities	Maintenance & operations	Facilities	Room	Staff & services
Pos_ame (β_1)	−0.31**		0.32*	0.02	0.16*	−0.01
Pos_ops (β_2)	−0.17	0.24*		0.18**	0.21**	0.20**
Pos_fac (β_3)	−0.18**	−0.11	0.32*		0.20**	−0.01
Pos_rm (β_4)	−0.19**	0.27*	0.57***	0.28***		−0.09
Pos_staff (β_5)	−0.19**	0.10	0.68***	0.12	0.09	
neg_ame (β_6)	0.67***		0.33*	0.19**	0.16*	0.21**
neg_ops (β_7)	0.38**	−0.06		−0.03	0.22**	0.18**
neg_fac (β_8)	0.23**	0.30**	0.34*		0.19**	−0.07
neg_rm (β_9)	0.28***	0.35**	−0.03	0.16*		0.08
neg_staff (β_{10})	0.26***	0.25*	0.39**	0.04	0.19**	
Sentiment (β_{11})		−0.05	−0.32*	0.03	0.22**	0.21**
Length (β_{12})		0.02	−0.38**	−0.05	0.21**	0.16*
Nights (β_{13})		0.35***	−0.04	0.15*	0.17*	0.18**

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8
Heterogeneity effect of the reflection of closed-form evaluations and open-ended comments on customers' overall satisfaction.

	Dependent variable: customer overall rating			
	Closed-form evaluations		Open-ended comments	
	Chain hotels	Independent hotels	Chain hotels	Independent hotels
Pos_ame (β_1)	0.13	0.14	0.22***	0.23***
Pos_ops (β_2)	0.08	0.06	0.05	0.07
Pos_fac (β_3)	0.07	0.12	0.17**	0.17**
Pos_rm (β_4)	0.31***	0.32***	0.20**	0.19**
Pos_staff (β_5)	0.26***	0.27***	0.23***	0.25***
neg_ame (β_6)	−0.22**	−0.21**	−0.04	−0.01
neg_ops (β_7)	−0.26***	−0.28***	−0.18**	−0.03
neg_fac (β_8)	−0.11	−0.20**	−0.07	−0.05
neg_rm (β_9)	−0.20**	−0.21**	−0.15*	−0.16*
neg_staff (β_{10})	−0.21**	−0.20**	−0.24***	−0.23***
Sentiment (β_{11})	0.30***	0.33***	0.35***	0.38***
Length (β_{12})	−0.18*	−0.17*	−0.22***	−0.26***
Nights (β_{13})	0.19*	0.18*		

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

direct, spillover, and heterogeneity effects. Our results partially support H4a. From the results of Table 6 and Table 7, we can find for staff and service attributes that there is a significant negative relationship between the positive evaluations and comments of that attribute regarding independent hotels ($\beta_5 = -0.19, p < 0.05$) in Table 7, but not for chain hotels ($\beta_5 = -0.12, p > 0.1$) in Table 6. This finding supports H4a in that the direct effect is more significant for independent hotels. That may be because the attribute is an experience attribute that arouses customers' emotions [85]. Customers would like to commend service providers and provide more detail as well as use more favorable wording to describe the satisfactory service they received from chain hotels.

The five attributes analyzed in this study can be categorized into two types: product-related attributes including amenities, facilities, and room, and service-related attributes including maintenance and operations and staff and service. By examining the results in greater depth, we find that all the spillover effects for the chain hotels exist within the same category. That is, customers tend to provide more details in the textual comments about attributes in the same category if they do not show their perceptions directly in the closed-form evaluations. That makes their comments and perceptions of the whole category of attributes comprehensive. However, for independent hotels, the spillover effects are more significant because these effects can cross different categories of attributes. For example, a closed-form negative evaluation of staff leads customers to comment more about the room for independent hotels only ($\beta 10 = 0.19, p < 0.05$) in Table 7. That is because independent hotels have more unique features, operations procedures, and standards than chain hotels. Thus, customers strive to provide more detailed reviews from a multidimensional perspective to offer more information to other customers. As a result, their reviews are more comprehensive and diverse. The differences between the results from chain hotels versus independent hotels support H4b that the spillover effect is more significant for independent hotels. Furthermore, for the coefficients that have the same level of significance, to test whether the coefficients in the models are statistically different between chain and independent hotels, we refer to previous studies (e.g., [52,73]) to adopt a cross-model Wald test. We find that the null hypothesis that the coefficients are the same between chain and independent hotel models cannot be rejected. This indicates the coefficients that are at the same significant level do not have significant differences.

The findings in Table 8 suggest that independent hotels receive more negative closed-form evaluations (e.g., facilities, $\beta_8 = -0.20, p < 0.05$) and fewer negative open-ended comments (e.g., maintenance and operations, $\beta_7 = -0.18, p < 0.05$only for chain hotels) of attributes that are found to significantly reflect overall negative customer satisfaction. Therefore, the heterogeneity effect is more significant for independent hotels and, thus, H4c is supported.

6. Theoretical and managerial implications

6.1. Theoretical implications

The theoretical background of this study lies in the theory of information diagnosticity and ambiguity [24] and three-factor theory [48]. Our findings in this study contribute to the existing literature in the following three ways.

First, previous studies about online customer reviews (e.g., [61,76]) mainly analyzed the contents of the reviews from the performance perspective; namely, they analyzed how the performance of various product or service attributes affected online customer review behavior and content. However, our study finds that how and what customers write in their reviews also depends on the design of the review system. We find that customers' closed-form evaluations affect their review behaviors in open-ended comments. Online reviews are an important information source for understanding customer perceptions. Our findings reveal the important role of the information disclosure design in affecting customers' information disclosure behavior.

Second, previous studies about the influence of the performance of various attributes on customer perception (e.g., [15,48]) categorized various attributes into excitement, basic, and performance factors based on three-factor theory. Our findings in this study enrich this field by offering an efficient way to identify those three categories of attributes. We find that category identification also depends on the form of the evaluation—whether it is a closed-form or open-ended comment. Further, we find that the relationship between the open-ended comments and customer overall satisfaction is more significant for the advantages of the attributes; however, the relationship between the closed-form evaluation and customer overall satisfaction is more significant for the disadvantages of the attributes. Thus, readers of reviews can better extract key information from online customer reviews and customers' revealed perceptions by reading positive textual comments and negative closed-form evaluations, alleviating information overload issues.

Third, based on the theory of information diagnosticity and ambiguity [24], previous studies (e.g., [19]) found that individuals strive to avoid or alleviate information ambiguity. Our study contributes to this field by finding relationships between customers' closed-form evaluations and open-ended comments, which they write to avoid information ambiguity. Customers attempt to put more effort into their reviews when they comment on product or service attributes offered by independent providers because the unique features and varied operational standards of the independent providers increase ambiguity, and that ambiguity encourages customers to put more effort into the diagnosis and reduction of information ambiguity.

6.2. Managerial implications

Managers have long realized the significant business value of online customer reviews for understanding, customer perception, and they have used the generated eWOM effects to enhance business performance. Based on customers' reviews, companies are improving their products and services. These improvements enhance customer perception through an essential approach. However, our findings reveal that how and what customers write in their online reviews are determined by not only the products and services offered but also the design of the online review systems. These findings should persuade companies to enhance their understanding of their customers by optimizing their review systems. A combination of closed-form evaluations and open-ended textual comments is helpful because those responses can help companies understand the keys to customer perceptions comprehensively. Additionally, companies can refer to more details from customers' textual comments if they want to conduct a more in-depth analysis. Companies can provide more options so that closed-form evaluations provide more details. As a result, companies can find merits to focus on and weaknesses to improve more directly. To avoid information overload and alleviate the spread of negative eWOM through online customer reviews, companies can set an appropriate upper limit to the textual comments. In this way, customers may focus on elaborating the reasons for their low satisfaction with certain attributes rather than use more words simply to complain or reveal their negative emotions.

Further, many managers today provide online managerial responses to customers. On the one hand, our findings suggest that a higher focus on the advantages of attributes positively reflects overall customer satisfaction. This encourages managers to focus not only on negative comments but also provide favorable feedback to customers who write detailed positive comments. In this way, managers can enhance customers' loyal behavior and encourage them to spread even more positive eWOM by writing online textual comments and enduring the associated hassle cost.

At the same time, customers' negative closed-form evaluations of attributes directly show their low satisfaction. This reveals the barrel principle, which states that it is the minimum, or the weakness, of certain aspects that determines the customers' overall perceptions rather than the maximum, or the strength. Therefore, managers can alleviate issues with information overload caused by substantial and unstructured reviews by focusing on the negative closed-form evaluations of certain attributes. This is a more efficient way for managers to allocate their time while extracting key information from reviews and taking corresponding actions such as online response, service recovery, and improvement.

Further, particularly for independent providers, managers should focus on customers' comments about their unique features and operations. Customers tend to offer more information about independent providers compared with chain providers because of customers' limited familiarity with independent providers. Benchmarking strategies can be implemented to analyze how customers feel about the providers and the providers' competitors. In this way, companies can better position themselves in the market and target customers' needs to make corresponding improvements. Further, various formats of information such as text descriptions, photos, and demo videos can be posted on websites to alleviate the information ambiguity customers perceive. In this way, customers can become more familiar with providers and reveal their perceptions more directly instead of providing information to other customers out of altruism.

7. Conclusions and directions for research

7.1. Conclusions

In this study, we examine how the different designs of online review systems, especially closed-form evaluations and open-ended textual comments, affect customers' online review writing behaviors and reflect satisfaction. We find the direct and spillover effects of online review behavior and the heterogeneity effect between the reflection of closed-form evaluations and open-ended comments on satisfaction.

In terms of the direct effect, we find that positive closed-form evaluations of attributes reduce customers' behaviors regarding writing details about those attributes in the open-ended comments, but negative closed-form evaluations of attributes increase this behavior. This finding shows that customers tend not to expand the descriptions of their positive feelings about attributes but often deliver their negative perceptions in detail. Additionally, we find that asymmetric effects exist for the direct effect; namely, the increasing effect of negative closed-form evaluations is greater than the reducing effect of positive closed-form evaluations.

In addition, we find the spillover effect exists. Findings suggest that the closed-form evaluations of certain attributes increase customers' behaviors regarding writing details about other attributes in open-ended comments.

Further, regarding the heterogeneity effect, we find that, for the advantages of the attributes, the open-ended comments about the attributes have a more significant effect than the closed-form evaluations of those attributes in reflecting overall customer satisfaction. That is, when the focus of the comments is higher, the customers have a higher overall satisfaction with the consumption experience. However, when customers indicate attribute-level satisfaction with a simple positive rating in the closed-form evaluation, that does not necessarily reflect overall customer satisfaction. Conversely, for the disadvantages of the attributes, the negative open-ended comments contain more noise when reflecting overall customer perceptions because the greater emphasis on the negative open-ended comments does not necessarily significantly negatively reflect customers' overall satisfaction. Comparatively, a negative closed-form evaluation is a direct way to show customers' low satisfaction with the overall consumption experience.

Finally, the direct, spillover, and heterogeneity effects of customers' evaluations of and comments about independent providers are more significant than those regarding chain providers. Our findings in this study reveal that the design of the online review system affects customers' review behaviors and their reflected satisfaction. Companies can use our findings to optimize their review system design and extract key information based on the reflection mechanism of customer perceptions corresponding to the design of the review system and, as a result, avoid information overload. In this way, companies can better understand customers' needs to improve their corresponding products and services, and they can generate online customer reviews and their generated eWOM effect to attract demand and enhance financial performance.

7.2. Directions for future research

In this study, we provide several directions for research. First, our study examines the role of closed-form evaluations and open-ended textual comments in reflecting customer satisfaction. Future studies can examine the design of the review system in reflecting customers' other perceptions, such as loyalty behavior (e.g., recommendations) and the willingness to pay a premium. Second, both platforms we examined belong to the same category—third-party booking platforms. Future studies can analyze how the properties of the platforms, namely, third-party platforms, social media, and firms' direct platforms, moderate the role of review system design in reflecting customer perception. Last, the different effects of online reviews and offline reviews, such as comment cards, mailings, phone calls, and oral conversations on reflecting customer perception can be examined.

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