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Determining investment allocation strategies to improve consumer satisfaction based on a preference learning model

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ABSTRACT

Mining product attribute performance, importance, and their (a)symmetric impacts on consumer satisfaction from online reviews is crucial for enterprises to formulate real-time investment allocation strategies for product improvement. While existing studies have employed machine learning, regression, and correlation analysis to explore these complex relationships, they face the challenge of balancing prediction accuracy with interpretability. This paper proposes an asymmetric importance-performance analysis model based on preference learning with online reviews. It devises an asymmetric value function incorporating unknown preference parameters to elucidate (a)symmetric impacts of attribute performance on overall consumer satisfaction. The process of learning preference parameters is implemented by mathematical programming with a simulation experiment. Attributes are classified into eight categories according to their performance and importance, each corresponding to an improvement strategy. An optimization model is constructed to develop investment allocation strategies for attribute improvement, aiming at maximizing consumer satisfaction within established financial constraints. A hotel-focused case study showcases the approach, and simulations validate the robustness of the proposed model.

1. Introduction

Consumer satisfaction analysis is an effective way to develop product improvement strategies, which in turn helps enterprises minimize costs, improve consumer repeat purchase rates, and enhance corporate profitability. A consumer's satisfaction with a product is a function of attribute performance and his/her preferences for different attributes (Song et al., 2024). Consumer preferences are usually reflected by the importance of attributes (Zhu et al., 2022). The impact of consumer preferences and attribute performance on consumer satisfaction is important in consumer research (Lu et al., 2023).

Importance-performance analysis (IPA) has been widely used for consumer satisfaction analysis because of its simplicity and ease of understanding (Dueñas et al., 2021). It aims to diagnose the strengths and weaknesses of products under different attributes and recommend the optimal allocation of limited resources to improve consumer satisfaction (Albayrak, 2015). However, the assumption in traditional IPA methods that the performance of attributes is linear to consumer satisfaction does not always conform to actual situations. The three-factor theory states that the importance of an attribute may vary depending on its performance. Considering the asymmetric effects of attribute performance on consumer satisfaction, the three-factor theory categorizes attributes into three groups: basic, excitement, and performance factors.[1] The three-factor theory helps to gain insights into the focus of product quality development and provides the possibility of creating differentiation to delight consumers (Zhang et al., 2023). Researchers have proved that combining the IPA with the three-factor theory (called asymmetric IPA) is effective in developing product improvement strategies (Li and Agyeiwaah, 2023).

In addition, obtaining effective product information and consumer preference information is the key to conducting asymmetric IPA. Previous studies have mainly collected information about the importance and performance of product attributes through surveys or experiments (Borgers and Vosters, 2011). Such types of data collection are both time-consuming and costly, as they require rigorous design and a proper questionnaire procedure to ensure the quality of responses. The emergence of large-scale online reviews provides another way for consumer satisfaction analysis (Zhang and Xu, 2024; Zhao and Huang, 2024).

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[1] Performance factors and attribute performance are different concepts. The former refers to a category of attributes, while the latter refers to the quality of attributes.

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Online reviews are positive or negative product evaluations posted by consumers on platforms in the form of ratings (e.g., 1 to 5-star ratings) or open-ended texts (Qahri-Saremi and Montazemi, 2023). Compared with the information obtained through questionnaires, online reviews have the advantages of large amounts of sampling, real-time data, easy collection, and wide coverage.

A few studies have employed online reviews to conduct (asymmetric) IPA analysis. Firstly, topic modeling algorithms, such as latent Dirichlet allocation (Li et al., 2024), were applied to extract product attributes that consumers prioritize. Subsequently, sentiment analysis was leveraged to quantify consumers' evaluations of these attributes, thereby reflecting their performance (Pan et al., 2023). Furthermore, methods such as correlation analysis, machine learning, and regression analysis were utilized to estimate attribute importance (or weights). Ultimately, (asymmetric) IPA analysis was conducted to find attributes that need improvement. Notably, accurate assessment of attribute importance is a pivotal aspect of this process, attracting researchers' attention. For example, Liu et al. (2024b) conducted a partial correlation analysis between overall consumer satisfaction (represented by overall star ratings) and satisfaction with individual product attributes (represented by attribute-level reviews), with the resulting coefficients implicitly signifying attribute importance. Bi et al. (2019) used Z neural networks with a hidden layer to estimate attribute weights based on input variables of attribute performance values determined by online reviews and output variables of corresponding online ratings. The attribute weights were determined by the connection weights between the input and output layers. To further enhance understanding of attribute interactions, Shin et al. (2024) introduced a machine learning approach leveraging the Shapley additive global importance method. Although machine learning exhibits advantages in processing large-scale data and possesses good fitness and prediction performance, the results tend to be less interpretable, making it difficult to intuitively reveal the nonlinear relationship between attribute performance and overall consumer satisfaction. To tackle this issue, scholars (Hu et al., 2020; Pan et al., 2023; Li et al., 2024) employed penalty-reward contrast analysis with a dummy regression analysis to differentiate the impact of attributes on overall ratings between low- and high-performance scenarios.

However, the regression model makes it difficult to embody consumers' preference structures. Specifically, regression coefficients fail to reveal internal mechanisms when reviewers weight various product attributes to form an overall evaluation. For instance, consumers have diverse focal points: some consider a hotel's price, service, and food, while others limit their opinions to bedrooms and service. Although regression analysis does not mandate uniformity in sample features (i.e., product attributes), the process of handling missing values or deleting important attributes mentioned only in some samples may distort the true relationship between overall star ratings and attribute-level reviews. Furthermore, overall star ratings are discrete data which could not accurately reflect the overall satisfaction levels and categorize products into multiple categories ranging from the least to the most satisfied. For instance, even if multiple hotels receive the same 4-star rating, the underlying satisfaction levels may vary, with some nearly at 3-star rating and others approaching to 5-star rating. Classification models exhibit greater effectiveness in revealing the evaluation rules expressed by consumers through online reviews compared to regression models. In addition, traditional (asymmetric) IPA focuses on developing improvement strategies based on the classification of attributes that have different impacts on consumer satisfaction, but few studies combined attribute importance, performance, and investment costs to develop investment allocation strategies for attribute improvement.

To address the aforementioned issues, this paper proposes a preference learning-based asymmetric IPA model within the context of online reviews. The core of this model lies in integrating machine learning with penalty-reward contrast analysis to capture the nonlinear relationship between attribute performance and overall consumer satisfaction from online reviews. This model not only visually presents the preference structures of consumers, enhancing model interpretability, but also ensures the robustness of results through k-fold cross-validation and simulation analysis. The main work is summarized as follows:

- Constructing an asymmetric value function for consumer preference modeling. Based on the three-factor theory and multi-attribute value theory (MAVT), a value function with unknown preference parameters (e.g., attribute weights) is designed to depict how attribute performance nonlinearly influences overall consumer satisfaction, thereby deeply analyzing the preference structures of consumers.
- Proposing a preference learning model with inconsistent attribute sets. The process of learning the preference parameters in the defined value function is implemented by mathematical programming, where each online review is used as a decision example for a sorting problem that classifies products into 1 to 5-star ratings based on attribute-level evaluations. Particular consideration is given to inconsistencies among attribute sets. This enables precise extraction of attribute weights under varying performance scenarios from online reviews. To obtain a robust result, we design a simulation experiment to determine a comprehensive preference model for consumer satisfaction analysis.
- Developing a product optimization strategy for resource allocation. Based on the estimated performance and importance of attributes, we divide them into eight categories, each corresponding to an improvement strategy. To further develop resource allocation strategies for attribute improvement, we formulate an optimization model aimed at maximizing consumer satisfaction within established financial constraints.

The rest of the paper is organized as follows. In Section 2, we briefly review the literature related to the asymmetric IPA and preference learning. Section 3 develops a preference learning-based asymmetric IPA model. A case study is elaborated based on hotel online reviews in Section 4. Research implications are presented in Section 5. Section 6 ends the paper with conclusions.

2. Literature review

2.1. Studies on consumer satisfaction analysis based on asymmetric IPA

To describe the (a)symmetric effects of attribute performance on overall consumer satisfaction, the IPA model has been improved based on the three-factor theory and designed a three-dimensional IPA plot, which jointly prioritizes attributes for improvement based on attribute performance, attribute importance, and satisfaction factors (Li and Agyeiwaah, 2023). Through penalty-reward contrast analysis, a reward index and a penalty index were estimated for each attribute by introducing dummy variables in the regression model to measure the effect of negative performance and positive performance on consumer satisfaction, respectively. Lai and Hitchcock (2016) summarized the asymmetric IPA studies published in 2014 and before and found that these studies mainly used questionnaires to obtain the information to be analyzed. Questionnaires are labor and financial-intensive, and the reliability of analysis results may be influenced by the subjective judgments of respondents (Bi et al., 2019).

We summarize the research advancements in asymmetric IPA from 2020 to 2024, as detailed in Table 1. In terms of data dimensionality, existing studies have broadened their scope to leveraging online reviews to mine product attribute performance and importance, enhancing the diversity and scale of data sources. These studies mainly rely on regression analysis to estimate attribute weights. However, as mentioned in the introduction, regression models struggle to explain the preference structures of consumers. In addition, treating online ratings as continuous numerical values while overlooking the uncertainty inherent in these ratings may influence the accuracy of the results. This paper proposes preference learning techniques (with detailed

Table 1
Research on asymmetric IPA from 2020 to 2024.

Ref.	Filed	Data source	Method to determine attribute importance	Improvement strategies
Sun et al. (2020)	Bus stop	Questionnaire	Regression analysis	Strategy intervals
Pratt et al. (2020)	Tourism	Questionnaire	Regression analysis	Strategy intervals
Cao et al. (2020)	Habitancy	Survey	Regression analysis	Strategy intervals
Hu et al. (2020)	Hotel	Online reviews	Regression analysis	Strategy intervals
Dueñas et al. (2021)	Destination	Questionnaire	Regression analysis	Strategy intervals
Tuan et al. (2022)	Transport	Questionnaire	Regression analysis	Strategy intervals
Li and Agyeiwaah (2023)	Education	Questionnaire	Data-centric calibration	Strategy intervals
Pan et al. (2023)	Restaurant	Online reviews	Regression analysis	Strategy intervals & the priority of attributes in the same interval
Wang and Jia (2024)	Construction	Questionnaire	Correlation analysis	Strategy intervals
Li et al. (2024)	Hospitality	Online reviews	Regression analysis	Strategy intervals
This paper	Hotel	Online reviews	Preference learning	Strategy intervals & investment allocation strategies

elaboration later) to delve deeply into consumer evaluation mechanisms from online reviews, intuitively presenting the nonlinear relationships among attribute performance, importance, and overall consumer satisfaction. This approach boasts both high robustness and interpretability.

2.2. Studies on preference learning methods

Consumer satisfaction analysis through online reviews can be viewed as a multi-attribute sorting problem (Alvarez et al., 2021), in which products described over a set of attributes are assigned into predefined homogenous groups (e.g., 1 to 5-star ratings). These groups are ordered from the most (5-star rating) to the least (1-star rating) preferred ones.

Preference learning provides an indirect preference elicitation framework for solving multi-attribute sorting problems. It aims to estimate decision-makers' preference models from holistic preferences on a set of reference alternatives or historical decision examples (Gehrlein et al., 2023). The principle of preference learning is similar to those of classification methods used in machine learning since they are all designed to learn classification models from training samples. The distinguishing characteristic of preference learning is that the learned preference model provides an intuitive interpretation of a decision-maker's value system, and the parameters in the model have practical meanings (Liu et al., 2023). In contrast, the classification methods used in machine learning are primarily concerned with determining an optimal model that fits as many samples as possible, but not with the interpretability of the learned model (Martyn and Kadziński, 2023).

The MAVT is considered one of the fundamental theories for constructing preference models (Dyer and Smith, 2021). It enables the modeling of uncertain preference information, facilitates updating preference models with new preference information, gives great mathematical freedom in describing stakeholder preferences, and has a reliable theoretical foundation and simple arithmetic process (Zheng and Lienert, 2018). The UTADIS (UTilités Additives DIScriminantes) (Zopounidis and Doumpos, 1999) is one of the most famous MAVT-based sorting methods. It aims to develop an additive value function for sorting purposes through linear programming (Alvarez et al., 2021). However, the UTADIS method and its extensions assume that attribute importance is independent of attribute performance. It goes against the three-factor theory and therefore is inappropriate to estimate the preference structures of consumers. To address this problem, we improve the UTADIS method with penalty-reward contrast analysis to conduct preference learning from online reviews.

3. The preference learning-based asymmetric IPA model with online reviews

This section presents a methodology to conduct asymmetric IPA through a preference learning method with online reviews. Table 2 illustrates the key notations used in the methodology which has three assumptions:

Assumption 1. Consumers evaluate a product based on the performance of product attributes and their preferences for different attributes.

Table 2
The key notations used in the methodology.

Notation	Description
$C = \{c_1, c_2, \cdots, c_n\}$	A family of product attributes that impact consumer satisfaction, where c_j is the j th attribute of the product.
$A = \{a_1, a_2, \cdots, a_m\}$	A set of online reviews of the product, where a_i is the i th online review; each online review includes an overall star rating $r(a_i)$, and a text review from which we can extract a sentiment value $t_j(a_i)$ for each attribute.
$U = \{u_j(a_i) \| j = 1, 2, \cdots, n; i = 1, 2, \cdots, m\}$	The utilities of different attributes determined by different online reviews, where $u_j(a_i)$ is the utility of the j th attribute determined by the i th online review. The overall value $U(a_i)$ of the product is an aggregation of attribute utilities.
$W = \left\{\left(w_j^{\mathrm{R}}, w_j^{\mathrm{P}}\right) \middle\| j = 1, 2, \cdots, n\right\}$	The reward and penalty indices of attributes, where w_j^{R} (or w_j^{P}) denotes the importance of the j th attribute when its performance is positive (or negative).

Assumption 2. Consumer preferences for a product attribute may vary depending on its performance.

Assumption 3. An online review includes a text review that assesses different attributes of a product, and a star rating that represents the overall consumer satisfaction.

The framework of the proposed methodology is shown in Fig. 1, which consists of three modules: 1) learning consumer preference models from online reviews, 2) prioritizing attributes through asymmetric IPA, and 3) determining attribute investment allocation strategies based on an optimization model. In the first module, online reviews are used to analyze the performance and importance of product attributes. Specifically, text reviews are converted into structured data through sentiment analysis to express attribute performance. A preference learning process is constructed to estimate consumer preference models based on the consistency between text reviews and star ratings on expressing consumer satisfaction. The robustness of the learning results is analyzed through simulations. On this basis, we analyze the reward index (*i.e.*, the importance of an attribute when its performance is positive) and the penalty index (*i.e.*, the importance of an attribute when its performance is negative) for each attribute. The second module is to determine the satisfaction factors of attributes based on the reward and penalty indices, and then perform asymmetric IPA to determine the prioritization of attributes for improvement by dividing attributes into eight categories based on satisfaction factors and attribute performance. In the third module, an optimization model is developed to determine the amount of investment to be allocated to each attribute in redesign, so that consumer satisfaction can be maximized with limited resources. These three modules are described in detail in Sect. 3.1, Sect. 3.2, and Sect. 3.3, respectively.

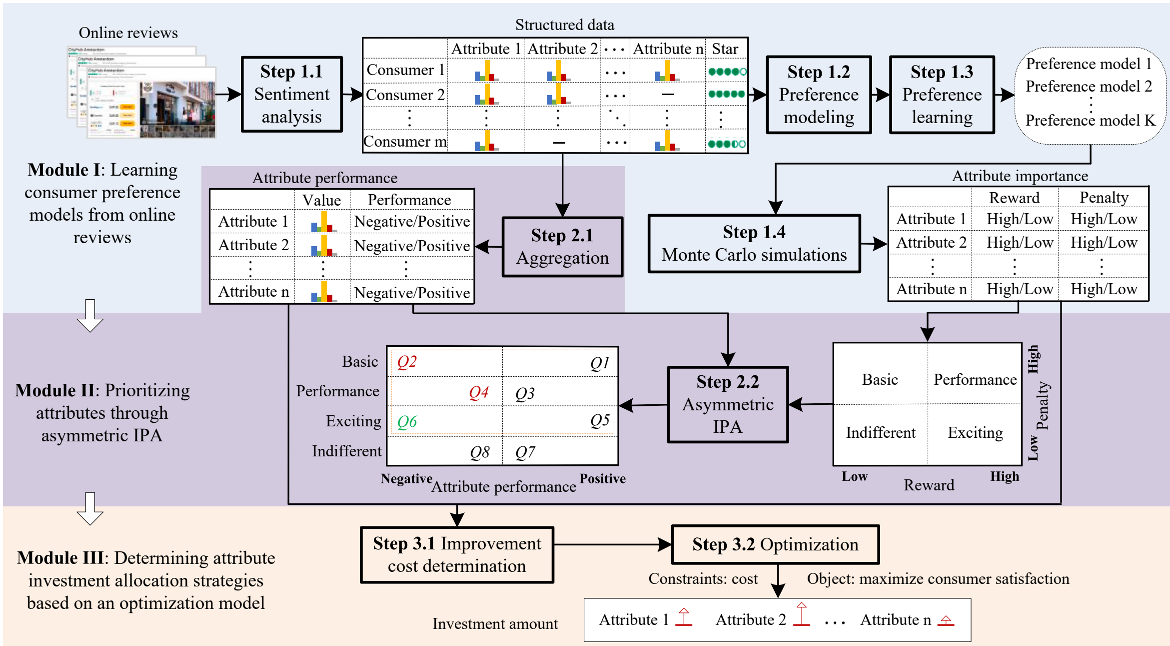

Fig. 1. The framework of the preference learning-based asymmetric IPA model with online reviews.

3.1. Module I: learning consumer preference models from online reviews

For Module I, we propose a preference learning method to estimate consumer preference models from online reviews. It consists of four steps. The specific content of each step is described in Sects. 3.1.1 to 3.1.4.

Step 1.1 (Sentiment analysis): Sentiment analysis is conducted on text reviews to extract sentiment tendencies and intensities towards various product attributes. The sentiment information is classified into five categories: "very negative" (*VN*), "negative" (*N*), "neutral" (*Ne*), "positive" (*P*), and "very positive" (*VP*).
Step 1.2 (Preference modeling): An asymmetric value function is proposed based on the MAVT and the three-factor theory to model the preference structure of consumers and reflect the mechanism by which consumers weigh product attributes during evaluation. This function characterizes the dynamic preference of consumers towards attributes.
Step 1.3 (Preference learning): A preference learning model based on mathematical programming is proposed, which establishes a fitting relationship between star ratings and attribute-level sentiment values through classification thresholds and estimation errors. Consumer preference models are estimated by multiple rounds of training and testing on online reviews.
Step 1.4 (Simulation): A simulation experiment is designed to verify the robustness of the learning results and determine a comprehensive preference model.

3.1.1. The process of sentiment analysis

Unlike the quantitative representation of star ratings, text reviews are unstructured and presented in the form of natural language. The process of extracting attribute information from text reviews consists of three main steps. Firstly, a Web crawler is used to crawl text reviews from websites; secondly, product attributes that have an impact on consumer satisfaction are identified through topic analysis and word embedding techniques (Hu et al., 2019); finally, sentiment analysis is performed to extract sentiment information and analyze attribute performance (Liu et al., 2024a). Four primary methods exist to represent sentiment tendencies and intensities in online reviews: 2-level (*N*, *P*), 3-level (*N*, *Ne*, *P*), 5-level (*VN*, *N*, *Ne*, *P*, *VP*), and 7-level (*VN*, *N*, *SN*, *Ne*, *SP*, *P*, *VP*), with "*SN*" indicating slightly negative and "*SP*" indicating slightly positive. A limited number of sentiment categories (e.g., 2-level) compromises classification fineness. Conversely, an excessive number, though enhancing nuanced sentiment capture, may influence accuracy. To balance, this paper adopts a five-level classification for characterizing the sentiment information in online reviews, which is also the way used by related literature (Bi et al., 2019; Shin et al., 2024).

In online reviews, multifaceted evaluations of a single attribute coexist, e.g., "*The hotel room is spacious but lacks sound insulation*". Summarizing these varied sentiments with a single intensity is inadequate. Thus, we introduce a linguistic representation model (see Eq. (1)) based on the distribution of sentiment intensities, quantifying frequencies/probabilities of various intensities to depict sentiment nuances. This approach can capture both the positive "*spacious room*" and negative "*inadequate sound insulation*" sentiments. To be specific, let $t_j(a_i)$ be the sentiment value of the j th attribute, as determined by the i th text review of a product, where s_α denotes a kind of sentiment intensity in $\{s_1 = VN, s_2 = N, s_3 = Ne, s_4 = P, s_5 = VP\}$. The set $\left\{p_1^{ij}, p_2^{ij}, \cdots, p_q^{ij}\right\}$ (here $q = 5$) describes the distribution of different sentiment intensities and p_α^{ij} represents the average closeness (probability) of sentiment words used to describe attribute c_j in the i th text review to sentiment intensity s_α. If c_j is mentioned in the i th text review, there is at least one probability p_α^{ij} whose value is larger than zero. In this case, the probabilities p_α^{ij} for $\alpha = 1, 2, \cdots, q$ are normalized such that $\sum_{\alpha=1}^{q} p_\alpha^{ij} = 1$. If c_j is not mentioned in the i th text review, there is no sentiment information about this attribute[2] and $t_j(a_i) = \varnothing$. In addition, the star rating of the product associated with the i th online review can be denoted as Eq. (2). There are preference relations among star ratings that $r(a_i) \succ r(a_v)$ ("$\succ$" means "is preferred to") iff $\beta_i > \beta_v$; $r(a_i) \sim r(a_v)$ ("$\sim$" means "is indifferent to") iff $\beta_i = \beta_v$, $\forall i, v \in \{1, 2, \cdots, m\}$.

[2] For example, through sentiment analysis on a hotel text review "*Clean, great location, excellent value for money*", we obtain the sentiment values of three hotel attributes "price", "cleanliness" and "location" as {*VN*: 0, *N*: 0, *Ne*: 0, *P*: 1, *VP*: 0}. There is no sentiment information of other hotel attributes such as "food".

$$t_j(a_i) = \begin{cases} \varnothing, \text{if } c_j \text{ is not commented in the } i\text{th text review} \\ \{p_\alpha^{ij} s_\alpha | \alpha = 1,2,\cdots,q\}, \text{otherwise} \end{cases}, \forall i,j \quad (1)$$

$$r(a_i) = \beta_i - \text{star rating}, \beta_i \in \{1,2,\cdots,g\}, \forall i \quad (2)$$

3.1.2. The process of preference modeling

As shown in Eq. (1), the sentiment value of an attribute is expressed as a probability distribution of all preference intensities. Similar to the expected utility theory, the score of a_i under the j th attribute can be defined as the weighted sum of the utility of each preference intensity, as shown in Eq. (3). The monotone increasing function $u: s_\alpha \rightarrow [0,1]$ for $\alpha = 1,2,\cdots,q$ is used to determine the utility of sentiment intensities, where $u(s_\alpha) > u(s_{\alpha'})$ iff $\alpha > \alpha'$, and $u(s_\alpha) = u(s_{\alpha'})$ iff $\alpha = \alpha'$, $\forall \alpha, \alpha' \in \{1,2,\cdots,q\}$. To distinguish positive and negative sentiments, we set $u(s_\alpha) = (\alpha - 1)/(q-1)$. In this setting, if a sentiment intensity s_α is "negative" or "very negative", then its utility is smaller than 0.5. If it is "positive" or "very positive", then its utility is larger than 0.5. In this way, we can judge that the sentiment value $t_j(a_i)$ tends to be positive if $u_j(a_i) \in (0.5, 1]$ and it tends to be negative if $u_j(a_i) \in [0, 0.5)$. We set $u_j(a_i) = \text{null}$, if attribute c_j is not mentioned in the i th text review.

$$u_j(a_i) = \sum_{\alpha=1}^{q} u(s_\alpha) \times p_\alpha^{ij}, \forall i,j \quad (3)$$

The score calculated by Eq. (3) portrays the desirability of the performance of a product on an attribute in the mind of the provider of the online review. The higher the score is, the better the performance is. In this sense, the score can be used to represent the performance of an attribute associated with an online review. According to the MAVT, a consumer's value system can be modeled by a value function that aggregates the performance values of different attributes and yields an overall performance value to indicate the desirability of the product in the mind of the consumer, which also reflects consumer satisfaction with the product. The essence of aggregation is to achieve trade-offs among attribute values. The additive value function uses attribute weights to portray consumers' preferences for attributes and assumes that the performance values of different attributes are additive. If a product is measured by all attributes c_j for $j = 1,2,\cdots,n$ and the weight w_j ($\sum_{j=1}^{n} w_j = 1$) of each attribute is constant, the overall performance value of the product can be defined as Eq. (4).

$$U_{additive}(a_i) = \sum_{j=1}^{n} w_j u_j(a_i) \quad (4)$$

However, according to the three-factor theory, the importance of an attribute may vary with its performance. Therefore, we define two independent indices (*i.e.*, the reward index w_j^{R} and the penalty index w_j^{P}) for each attribute to indicate its importance corresponding to positive and negative attribute performance, respectively. Let $w_j^{\mathrm{R}} \in [0,1]$ and $w_j^{\mathrm{P}} \in [0,1], \forall j$. The larger the value of w_j^{R} (or w_j^{P}) is, the greater the impact of the positive (or negative) performance of attribute c_j on the product's overall performance value should be. To depict whether an attribute exhibits a positive or negative performance, we introduce a set of indicator variables R_{ij} and P_{ij} for $i = 1,2,\cdots,m$ and $j = 1,2,\cdots,n$. If the attribute performance is positive (*i.e.*, $u_j(a_i) \geq 0.5$), then, $R_{ij} = 1$; otherwise, $R_{ij} = 0$. If the attribute performance is negative (*i.e.*, $u_j(a_i) < 0.5$), then $P_{ij} = 1$; otherwise, $P_{ij} = 0$. There is $R_{ij} + P_{ij} = 1$.

In addition, consumers usually do not evaluate all attributes of a product in their online reviews but rather focus on evaluating the attributes they consider important. Since different consumers value different product attributes, the attributes mentioned in online reviews may differ. To depict whether an attribute is mentioned in an online review, we introduce another set of indicator variables d_{ij} for $i = 1,2,\cdots,m$ and $j = 1,2,\cdots,n$. We set $d_{ij} = 1$ when attribute c_j is mentioned in the i th text review; otherwise, $d_{ij} = 0$.

Taking into account the dynamic weights of attributes and the inconsistency of attribute sets, we propose an asymmetric value function as shown in Eq. (5) to model consumers' preference structures, where $U(a_i)$ denotes the overall performance value of a product determined by the i th text review. The auxiliary variables γ_i for $i = 1,2,\cdots,m$ are defined for normalization such that $\sum_{j=1}^{n} \gamma_i \left(R_{ij} w_j^{\mathrm{R}} d_{ij} + P_{ij} w_j^{\mathrm{P}} d_{ij} \right) = 1$, where the value $\gamma_i R_{ij} w_j^{\mathrm{R}} d_{ij}$ (or $\gamma_i P_{ij} w_j^{\mathrm{P}} d_{ij}$) represents the weight of attribute c_j in the i th text review when its performance is positive (or negative). We have $U(a_i) \in [0,1]$. A higher value of $U(a_i)$ indicates better performance of the product, which means greater consumer satisfaction.

$$U(a_i) = \sum_{j=1}^{n} \gamma_i \left(R_{ij} w_j^{\mathrm{R}} d_{ij} + P_{ij} w_j^{\mathrm{P}} d_{ij} \right) u_j(a_i) \quad (5)$$

3.1.3. The process of preference learning

The proposed value function can reflect consumers' preferences through preference parameters (*i.e.*, the reward index w_j^{R} and the penalty index w_j^{P} for $j = 1,2,\cdots,n$). By determining the preference parameters, an exact value function can be obtained to represent consumers' preference structures. This section aims to discuss how to determine the values of these preference parameters based on historical decision examples (*i.e.*, online reviews) provided by consumers.

During the evaluation process through online reviews, consumers assess the performance of a product in various attributes and assign a star rating to indicate their overall satisfaction. According to consumer evaluations of product attributes, the overall performance value, as defined by Eq. (5), can indirectly indicate a consumer's overall satisfaction with the product. Additionally, the overall star rating provided by the consumer directly reflects his/her overall satisfaction. Therefore, there is a relationship between the calculated overall performance value and the overall star rating.

Overall performance values are continuous, while star ratings are discrete categories. Without loss of generality, we can deem that when an overall performance value falls within a certain range, it corresponds to a specific star rating. Let μ_β be the classification threshold associated with β-star rating, for $\beta = 1,2,\cdots,g$. We have $\mu_1 < \mu_2 < \cdots < \mu_g$. Assume that $U(a_i) \geq \mu_1$ for all a_i, and we define $U(a_i) \leq \mu_{g+1}$ for all a_i. Since $U(a_i) \in [0,1]$, we can set $\mu_1 = 0$ and $\mu_{g+1} = 1$ without loss of generality. According to the UTADIS method, the assignment rule can be defined as follows: for all a_i,

$$a_i \text{ is with } \beta - \text{star rating iff } \mu_\beta \leq U(a_i) < \mu_{\beta+1}, \text{for all } \beta = 1,2,\cdots,g \quad (6)$$

There may be estimation errors regarding the overall performance value since the defined value function may not fully reflect consumers' preference structures or there is a bias between the text reviews and star ratings given by a consumer. The overestimation error σ_i^+ (or underestimation error σ_i^-) occurs when the upper (or lower) bound of the star rating is violated. For all a_i, we have

$$\begin{cases} U(a_i) - \mu_\beta + \sigma_i^- \geq 0 \\ U(a_i) - \mu_{\beta+1} - \sigma_i^+ < 0 \end{cases}, \text{if } a_i \text{ is with } \beta - \text{star rating, for all } \beta = 1,2,\cdots,g \quad (7)$$

This paper considers a preference model that is composed of an asymmetric value function and a set of classification thresholds. When a preference model is identified, the star rating of any product can be estimated. We take m_{train} online reviews $A_{train} = \left\{ \left(r(a_i), t_j(a_i) \right) \middle| j = 1,2,\cdots,n, i = 1,2,\cdots,m_{train} \right\}$ ($A_{train} \subseteq A$) of the product as a training set. A specific preference model can be estimated by solving the following mathematical programming model that minimizes the average estimation errors.

Model 1. min $F = \frac{1}{m_{train}} \sum_{\forall a_i \in A_{train}} \left(\sigma_i^+ + \sigma_i^- \right)$.

$$s.t.\begin{cases} \begin{cases} U(a_i) - \mu_\beta + \sigma_i^- \geq \delta_1 \\ U(a_i) - \mu_{\beta+1} - \sigma_i^+ \leq -\delta_2 \end{cases}, \text{if } a_i \text{ is with } \beta-\text{star rating}, \beta \in \{1,2,\cdots,g\}, \forall a_i \in A_{train} & (1-1) \\ U(a_i) = \sum_{j=1}^{n} \gamma_i \left(R_{ij} w_j^{\mathrm{R}} d_{ij} + P_{ij} w_j^{\mathrm{P}} d_{ij}\right) u_j(a_i), \forall a_i \in A_{train} & (1-2) \\ \sum_{j=1}^{n} \gamma_i \left(R_{ij} w_j^{\mathrm{R}} d_{ij} + P_{ij} w_j^{\mathrm{P}} d_{ij}\right) = 1, \forall a_i \in A_{train} & (1-3) \\ \mu_{\beta+1} - \mu_\beta \geq \mu, \forall \beta \in \{1,2,\cdots,g\} & (1-4) \\ 0 \leq \mu_\beta \leq 1, \mu_1 = 0, \mu_{\beta+1} = 1, \forall \beta \in \{1,2,\cdots,g\} & (1-5) \\ w \leq w_j^{\mathrm{R}} \leq 1, \forall j \in \{1,2,\cdots,n\} & (1-6) \\ w \leq w_j^{\mathrm{P}} \leq 1, \forall j \in \{1,2,\cdots,n\} & (1-7) \\ \sigma_i^+ \geq 0, \sigma_i^- \geq 0, \forall a_i \in A_{train} & (1-8) \end{cases}$$

The decision variables of Model 1 include 1) the reward and penalty indices of each attribute, *i.e.*, $w_j^{\mathrm{R}}, w_j^{\mathrm{P}}, j = 1,2,\cdots,n$; 2) the thresholds that define the lower and upper limits of each star rating, *i.e.*, μ_β, $\beta = 1,2,\cdots,g$; and 3) the overestimation and underestimation errors of each online review in the training set, *i.e.*, σ_i^+, σ_i^-, $i = 1,2,\cdots,m_{train}$. The parameters w, δ_1, δ_2, and μ are user-defined positive constants. The parameter w represents the minimum weight of each attribute. The parameter δ_1 (or δ_2) is used to limit the overall performance value to strictly greater (or smaller) than the lower (or upper) limit of each category. The parameter μ represents the minimum difference between adjacent classification thresholds that define the lower and upper limits of each star rating, and $\mu > \delta_1, \delta_2$.

The first constraint (1-1) is the core constraint of Model 1. It describes the correlation between overall performance values, overall star ratings, and estimation errors. The second constraint (1-2) is defined using a value function that establishes the relationship between the overall performance value of a product and its attribute-level values. The third constraint (1-3) is about the normalization of the reward and penalty indices. The fourth constraint (1-4) defines the minimum difference between adjacent classification thresholds. The last four constraints (1-5)-(1–8) define the value range of the three kinds of decision variables.

Model 1 is a quadratically constrained programming problem with continuous decision variables. It always has a solution since each fitting equation is associated with a slack variable (*i.e.*, estimation error) and the objective function represents the average of all slack variables. Existing solvers (such as Gurobi) are capable of supporting the solution of Model 1 under large-scale datasets. An optimal value of 0 for Model 1 indicates the presence of multiple preference models compatible with all the online reviews used for training. An optimal value greater than 0 for Model 1 signifies a singular preference model that exhibits the optimal fit to the training data. In scenarios involving the processing of large-scale training data, ensuring that all data strictly adhere to the constraints defined by Eq. (6) poses challenges due to the diversity of the data. This data inconsistency often leads to errors in the estimation process, resulting in a positive optimal solution for Model 1.

Traditional preference disaggregation analysis generally uses all decision examples to construct a training set from which an optimal preference model is extracted, but it does not test the prediction ability of the estimated preference model. Motivated by the cross-validation approach used in machine learning, we employ a training and testing process to learn preference models from online reviews, as described below.

i. All online reviews in the set A are randomly split into a training set A_{train} (with m_{train} online reviews) and a testing set A_{test} (with m_{test} online reviews), where $A_{train} \cup A_{test} = A$.
ii. Model 1 is used to estimate a preference model based on the training set.
iii. The prediction and fitting ability of the estimated preference model are, respectively, determined based on estimation errors on the testing set (see Eq. (8)) and on the whole set (see Eq. (9)). The smaller the estimation errors are, the higher the prediction or fitting ability of the model is.

$$Prediction = 1 - \frac{1}{m_{test}} \sum_{a_i \in A_{test}} \left(\sigma_i^+ + \sigma_i^-\right) \tag{8}$$

$$Fitting = 1 - \frac{1}{m} \sum_{a_i \in A} \left(\sigma_i^+ + \sigma_i^-\right) \tag{9}$$

iv. The training and testing process mentioned above is repeated multiple times (represented as L times). Each iteration uses different ratios (such as 5:5, 6:4, and 7:3) to divide online reviews in the training and testing sets.

Through the above preference learning process, L number of preference models are generated. However, these preference models are not always consistent due to consumers' individual preferences. Let w_{jl}^{R} and w_{jl}^{P}, respectively, be the reward and penalty indices of attribute c_j estimated in the l th training session for $j = 1,2,\cdots,n$, $l = 1,2,\cdots,L$. To make these indices derived from different training sessions comparable, we normalize them by Eq. (10) such that the most important attribute weights 1.

$$\overline{w}_{jl}^{\mathrm{R}} = \frac{w_{jl}^{\mathrm{R}}}{\max\limits_j w_{jl}^{\mathrm{R}}}, \overline{w}_{jl}^{\mathrm{P}} = \frac{w_{jl}^{\mathrm{P}}}{\max\limits_j w_{jl}^{\mathrm{P}}}, \forall j \tag{10}$$

3.1.4. Robustness analysis through simulations

A "mean" preference model can be constructed by averaging the preference parameters obtained from multiple trainings. Yet, when the training results lack robustness, it becomes challenging for the mean values of the preference parameters to accurately represent their true values. In such scenarios, the "mean" preference model is deficient in representativeness. This part aims to verify the representativeness of the "mean" preference model obtained from the training process through simulations. It also explores the construction of a preference model to comprehensively characterize consumers' preference structures in two scenarios: when the "mean" preference model is representative and when it is not.

According to the central limit theorem, a large number of training results for a preference parameter conform to a normal distribution. Therefore, we estimate each preference parameter based on their confidence intervals. We randomly generate 10,000 sets of preference parameters to perform simulations, where each preference parameter belongs to its confidence interval. Each set of preference parameters organizes a preference model. These preference models can be regarded as approximations of the "mean" preference model. If these preference models have strong fitting abilities, it indicates that the "mean" preference model is representative and the training results are robust.

Let σ_{it}^{+} and σ_{it}^{-}, respectively, be the overestimation and underestimation errors of the t th preference model generated in simulations corresponding to the i th online review. The fitting ability can be defined as:

$$Fitting_t = 1 - \frac{1}{m}\sum\nolimits_{a_i \in A}\left(\sigma_{it}^{+} + \sigma_{it}^{-}\right) \tag{11}$$

To judge the robustness of the training results, we compare the fitting ability (*i.e.*, $Fitting_t$ for $t = 1, 2, \cdots, 10000$) of the preference models generated in simulations and that (*i.e.*, $Fitting_l$ for $l = 1, 2, \cdots, L$) of the preference models obtained from the training process, as follows:

(1) If $\max_t Fitting_t \geq \min_l Fitting_l$, *i.e.*, the fitting ability of preference models derived from simulations may not always be inferior to that of preference models obtained from the training process, then the "mean" preference model is representative. In this case, the overall reward index $\overline{w}_j^{\mathrm{R}}$ and penalty index $\overline{w}_j^{\mathrm{P}}$ of each attribute can be estimated by:

$$\overline{w}_j^{\mathrm{R}} = \frac{1}{L}\sum\nolimits_{l=1}^{L}\overline{w}_{jl}^{\mathrm{R}}, \overline{w}_j^{\mathrm{P}} = \frac{1}{L}\sum\nolimits_{l=1}^{L}\overline{w}_{jl}^{\mathrm{P}}, \forall j \tag{12}$$

(2) If $\max_t Fitting_t < \min_l Fitting_l$, then the "mean" preference model is not representative and the training results are not robust. In this scenario, for the comprehensive development of a preference model, we compromise the accuracy of attribute weight estimation. More specifically, we analyze the frequency at which an attribute is estimated as "important" in the training process to determine the reward and penalty indices for it. Through the normalization by Eq. (10), the reward and penalty indices take values from 0 to 1. The middle point 0.5 can classify attributes into two categories, *i.e.*, attributes with a high importance level and attributes with a low importance level. If $\overline{w}_{jl}^{\mathrm{R}} \geq 0.5$, then we set $I\left(\overline{w}_{jl}^{\mathrm{R}} \geq 0.5\right) = 1$; otherwise, $I\left(\overline{w}_{jl}^{\mathrm{R}} \geq 0.5\right) = 0$. If $\overline{w}_{jl}^{\mathrm{P}} \geq 0.5$, we set $I\left(\overline{w}_{jl}^{\mathrm{P}} \geq 0.5\right) = 1$; otherwise, $I\left(\overline{w}_{jl}^{\mathrm{P}} \geq 0.5\right) = 0$. The overall reward (or penalty) index of an attribute can be determined by the frequency that its estimated index is greater than 0.5 among the L training sessions, as shown below:

$$\overline{w}_j^{\mathrm{R}} = \frac{1}{L}\sum\nolimits_{l=1}^{L} I\left(\overline{w}_{jl}^{\mathrm{R}} \geq 0.5\right), \overline{w}_j^{\mathrm{P}} = \frac{1}{L}\sum\nolimits_{l=1}^{L} I\left(\overline{w}_{jl}^{\mathrm{P}} \geq 0.5\right), \forall j \tag{13}$$

3.2. Module II: prioritizing attributes through asymmetric IPA

For Module II, we implement a symmetrical IPA that considers the varying impacts of different attributes on consumer satisfaction. The analysis takes into account the importance and performance levels of these attributes. It divides them into eight categories: must-be factors with positive performance, must-be factors with negative performance, performance factors with positive performance, performance factors with negative performance, excitement factors with positive performance, excitement factors with negative performance, indifferent factors with positive performance, and indifferent factors with negative performance. Each category corresponds to specific improvement strategies. There are two steps: Steps 2.1 and 2.2. The specific content of each step is described in Sects. 3.2.1 and 3.2.2.

Step 2.1 (Aggregation): An aggregation operator is introduced to integrate the sentiment tendencies and intensities of consumers towards various attributes presented in different online reviews.
Step 2.2 (Asymmetric IPA): Based on the asymmetric IPA, principles are established for determining satisfaction factors and the priority order of attributes for improvement.

3.2.1. The process of determining attribute performance

The performance of a product under different attributes can be estimated by consumers' evaluations. The more positive the evaluation is, the better the attribute performance is. Consumers may have different sentiment tendencies and intensities about the same attribute of a product. The performance of an attribute can be estimated by aggregating its sentiment scores determined by different online reviews, as defined by Eq. (14), where m_j is the number of online reviews that mention attribute c_j. If c_j is not mentioned in the i th online review, we set $u_j(a_i) = 0$. We have $Performance_j \in [0, 1]$. If $Performance_j \geq 0.5$, the performance of c_j is positive; otherwise, it is negative.

$$Performance_j = \frac{1}{m_j}\sum\nolimits_{i=1}^{m} u_j(a_i), \forall j \tag{14}$$

3.2.2. The process of the asymmetric IPA

The reward index indicates the importance level of attributes when their performance is positive and the penalty index quantifies their importance in cases of negative performance. Based on the values of these two indices estimated by preference learning, we can divide attributes into four satisfaction factors, namely, must-be factors, performance factors, excitement factors, and indifference factors. The classification principles are as follows:

i. Must-be factors ($\overline{w}_j^{\mathrm{R}} < 0.5$ and $\overline{w}_j^{\mathrm{P}} \geq 0.5$). The attribute importance level is low when the attribute performance is positive, and high when the attribute performance is negative.
ii. Performance factors ($\overline{w}_j^{\mathrm{R}} \geq 0.5$ and $\overline{w}_j^{\mathrm{P}} \geq 0.5$). The attribute importance level is high regardless of the attribute performance.
iii. Excitement factors ($\overline{w}_j^{\mathrm{R}} \geq 0.5$ and $\overline{w}_j^{\mathrm{P}} < 0.5$). The attribute importance level is high when the attribute performance is positive, and low when the attribute performance is negative.
iv. Indifferent factors ($\overline{w}_j^{\mathrm{R}} < 0.5$ and $\overline{w}_j^{\mathrm{P}} < 0.5$). The attribute importance level is low regardless of the attribute performance.

The four satisfaction factors have different impacts on consumer satisfaction. The negative performance of some attributes does not significantly reduce consumer satisfaction, while the positive performance of some attributes does not significantly increase consumer satisfaction. To identify to-be-improved attributes to enhance consumer satisfaction, we further classify attributes into eight categories based on both satisfaction factors and performance. Different categories have different improvement strategies and priorities, as described below:

i. Must-be factors with positive performance ($\overline{w}_j^{\mathrm{R}} < 0.5$, $\overline{w}_j^{\mathrm{P}} \geq 0.5$ and $Performance_j \geq 0.5$). Improving the performance of such attributes does not significantly increase the overall satisfaction of consumers. Therefore, managers can maintain or even reduce their investment in these attributes with limited resources to keep attribute performance at the minimum threshold of consumer expectations.

ii. Must-be factors with negative performance ($\overline{w}_j^{\mathrm{R}} < 0.5$, $\overline{w}_j^{\mathrm{P}} \geq 0.5$ and $Performance_j < 0.5$). Such attributes can greatly reduce overall satisfaction. Therefore, managers need to invest more in such attributes to make them perform to the expectations of consumers.
iii. Performance factors with positive performance ($\overline{w}_j^{\mathrm{R}} \geq 0.5$, $\overline{w}_j^{\mathrm{P}} \geq 0.5$ and $Performance_j \geq 0.5$). Such attributes make an important contribution to ensuring overall satisfaction. Reducing or increasing investment in such attributes can reduce or increase the overall satisfaction to the same extent. Therefore, managers should use their budgets to determine whether to pursue improvement strategies for such attributes.
iv. Performance factors with negative performance ($\overline{w}_j^{\mathrm{R}} \geq 0.5$, $\overline{w}_j^{\mathrm{P}} \geq 0.5$ and $Performance_j < 0.5$). Such attributes are the main factors that lead to consumers' dissatisfaction with the product. Improving the performance of such attributes can enhance overall satisfaction. Therefore, managers can invest more in these attributes to implement improvement strategies.
v. Excitement factors with positive performance ($\overline{w}_j^{\mathrm{R}} \geq 0.5$, $\overline{w}_j^{\mathrm{P}} < 0.5$ and $Performance_j \geq 0.5$). This type of attribute is similar to performance factors with positive performance. They are important factors in consumer satisfaction, and their continuous innovation and improvement can lead to higher levels of consumer satisfaction.
vi. Excitement factors with negative performance ($\overline{w}_j^{\mathrm{R}} \geq 0.5$, $\overline{w}_j^{\mathrm{P}} < 0.5$ and $Performance_j < 0.5$). Although such attributes are not major factors in consumer dissatisfaction and they are not attributes that must be improved, their innovation and improvement can greatly increase overall satisfaction. Therefore, managers can use them as core investments in addition to must-be and performance factors with negative performance.
vii. Indifferent factors with positive performance ($\overline{w}_j^{\mathrm{R}} < 0.5$, $\overline{w}_j^{\mathrm{P}} < 0.5$ and $Performance_j \geq 0.5$). Although such attributes perform well, they do not contribute much to enhancing the overall satisfaction. Managers should avoid over-investing in such attributes.
viii. Indifferent factors with negative performance ($\overline{w}_j^{\mathrm{R}} < 0.5$, $\overline{w}_j^{\mathrm{P}} < 0.5$ and $Performance_j < 0.5$). Although such attributes perform poorly, they are not the main cause of consumers' dissatisfaction. Improvements in their performance hardly enhance the overall satisfaction. In other words, the return on investment is low. Therefore, managers do not need to pay undue attention to such attributes.

In summary, when the performance of attributes is negative, the priority order for improvement is: must-be factors/performance factors $\succ$ excitement factors $\succ$ indifferent factors, and the priority relation between must-be factors and performance factors depends on their levels of importance. When the performance of attributes is positive, the priority order for improvement is: performance factors/excitement factors $\succ$ must-be factors $\succ$ indifferent factors, and the priority relation between performance factors and excitement factors depends on their levels of importance. While the prioritization of attributes to be improved is clear through categorization, with limited investment budgets, it is important to determine how much to invest in each attribute to maximize consumer satisfaction. This issue will be addressed in the next section.

3.3. Module III: determining product improvement strategies based on an optimization model

For Module III, we discuss how to determine the investment amount for each attribute based on costs, attribute importance, and attribute performance. There are two steps: Steps 3.1 and 3.2. The specific content of each step is described in Sects. 3.3.1 and 3.3.2.

Step 3.1 (Cost determination): We discuss how to guide decision-makers in determining the costs required to improve one unit of attribute performance.
Step 3.2 (Optimization): An optimization model is developed to determine product improvement strategies.

3.3.1. The process of determining improvement costs

Decision-makers need to determine the investment required to improve the performance of each attribute by one level. By establishing a correlation between sentiment intensity and performance values, the cost of a unit increase in attribute performance can be ascertained. Without loss of generality, the correspondence between sentiment intensities and performance values can be expressed as: very negative $\Leftrightarrow [0, 0.2)$, negative $\Leftrightarrow [0.2, 0.4)$, neutral $\Leftrightarrow [0.4, 0.6)$, positive $\Leftrightarrow [0.6, 0.8)$, and very positive $\Leftrightarrow [0.8, 1]$. The median value of each interval is 0.1, 0.3, 0.5, 0.7, and 0.9, respectively. In this regard, the average difference between adjacent performance species is 0.2. For instance, if it costs 10,000$ more per month to raise a hotel's service performance from neutral to positive, then the cost of raising one unit of service performance is 50,000$ (*i.e.*, $10,000/0.2$).

3.3.2. The process of determining the investment amount

Let $Cos\ t_j$ be the "spent" (or "saved") cost to improve (or reduce) the performance of attribute c_j by one unit, $Performance_j$ be the current performance of c_j, and $Performance_j^I$ be the performance of c_j after implementing the improvement strategy. If the investment in c_j is increased, then $Performance_j^I > Performance_j$; if the investment in c_j is decreased, then $Performance_j^I < Performance_j$; otherwise, $Performance_j^I = Performance_j$. Let H_j and K_j be indicator variables: if $Performance_j^I \geq 0.5$, then $H_j = 1$ and $K_j = 0$; if $Performance_j^I < 0.5$, then $H_j = 0$ and $K_j = 1$.

According to the MAVT, consumer satisfaction with a product after implementing the improvement strategy can be represented by[3] Eq. (15). The larger the value of *Satisfaction* is, the greater the consumer satisfaction is. The total cost to improve the performance of attributes can be expressed as Eq. (16).

$$Satisfaction = \sum_{j=1}^{n} \left(\overline{w}_j^{\mathrm{R}} H_j Performance_j^I + \overline{w}_j^{\mathrm{P}} K_j Performance_j^I \right) \tag{15}$$

$$Cost = \sum_{j=1}^{n} Cos\ t_j \times \left(Performance_j^I - Performance_j \right) \tag{16}$$

Let C be the total investment for product improvement. An optimization model can be established as Model 2 to determine the investment amount of each attribute to improve overall satisfaction. The objective function is to maximize consumer satisfaction. The primary constraint is the total cost. Other constraints can be added according to the actual situation, such as controlling the investment cost of individual attributes. In addition, based on the priority order for improvement discussed in Sect. 3.2.2, we can determine the corresponding constraints. For example, we can add a constraint $Performance_j^I \geq 0.5$ if attribute c_j is a must-be or excitement factor, $Performance_j^I > Performance_j$ if c_j is a performance factor, and $Performance_j^I \leq Performance_j$ if c_j is an indifferent factor.

Model 2. Max $Satisfaction = \sum_{j=1}^{n} \left(\overline{w}_j^{\mathrm{R}} H_j Performance_j^I + \overline{w}_j^{\mathrm{P}} K_j Performance_j^I \right)$.

[3] We do not normalize attribute weights to make the sum of weights being 1 here because the use of normalized weights does not affect the judgment of consumer satisfaction, but only the range of performance values.

$$s.t. \sum_{j=1}^{n} Cos\ t_j \times \left(Performance_j^I - Performance_j\right) \leq C.$$

4. Case study: developing improvement strategies for hotels

4.1. Data collection and preprocessing

The hospitality industry, a pivotal segment of the service sector, is experiencing unparalleled growth prospects fueled by globalization and tourism expansion. Identifying service quality shortcomings and implementing enhancements is crucial for hotels to secure a competitive edge. This case study delves into devising investment allocation strategies tailored to optimize hotel attributes informed by online reviews. We focus on twenty hotels (H1-H20) in Amsterdam, the Netherlands. Through a Web crawler (http://www.houyicaiji.com/), the data were collected from TripAdvisor which is the world's leading travel website with a huge amount of travel information and online reviews from all over the world. In total, we got 16,321 online reviews expressed in English over the past five years.

According to previous literature (Cheng and Jin, 2019; Hu et al., 2019) on the topic analysis of hotels, we selected 10 attributes for consumer satisfaction analysis on hotels, including "service", "food", "price", "cleanliness", "location", "decoration", "Internet", "bedroom", "bathroom", and "recreation". We utilized the word2vec model (Mikolov et al., 2013) to identify attribute keywords in online reviews through a shallow two-layer neural network. The model infers similarity based on co-occurrence frequency, allowing us to input an attribute and assess its associations with other terms, yielding a list of highly relevant keywords. After the manual screening, irrelevant words like "Tuesday" in the "price" category and "very" in the "cleanliness" category, which were not directly and uniquely associated with the relevant attributes, were removed. The refined keyword list is presented in Table A.1 in the Appendix.

We conducted sentiment analysis on each text review of a hotel to obtain the sentiment values of hotel attributes based on Stanford CoreNLP package. It includes the following steps to determine the sentiment value of a specific attribute: 1) dividing each text review into multiple sentences based on punctuation; 2) gathering sentences that contain one or more keywords related to the attribute; 3) identifying the grammatical structure, sentiment words, and their categories for the collected sentences; 4) calculating the proximity of sentiment words within each collected sentence to five basic sentiment categories (*e.g.*, VN, N, Ne, P, VP) to determine the distribution of sentiment intensities. Following this, the distribution information determined by the collected sentences is aggregated to derive the distribution of sentiment intensities specific to the attribute.

Based on sentiment analysis results, we then filtered the initial online reviews in two ways: 1) deleting records that do not contain sentiment information about any one of the 10 attributes, and 2) removing records whose star ratings are inconsistent with the sentiments of their text reviews, such as those where the sentiment information for all attributes is negative, yet the overall rating is given as 5-star rating, or those where the sentiment information for all attributes is positive, yet the overall rating falls within the 1- or 2-star range. It is noteworthy that the inconsistency between star ratings and the sentiment of text reviews may stem from technical errors in the process of sentiment analysis or maybe the deliberate result of consumers' subjective intentions. Although online reviews of the latter type are valuable for delving into consumer behaviors, given that the core objective of this paper is to extract consumer preference models from consistent information, we intend to exclude inconsistent information. Finally, 15,527 online reviews were obtained for data analysis, and their basic information is shown in Table 3.

The twenty hotels have overall star ratings ranging from 2.5 to 5, and the online reviews of these hotels range from 183 to 1742. The frequencies of different attributes mentioned in online reviews are different and smaller than 1, which indicates that not all attributes are mentioned in each online review and consumers focus on different attributes for different hotels. The attributes frequently mentioned in online reviews are crucial to consumer satisfaction (Shin et al., 2024). In other words, if a particular attribute is infrequently mentioned in online reviews of a hotel, it can be inferred that this attribute has not emerged as a point of concern or evaluation for the majority of consumers of that hotel. It is noteworthy that the weight of an attribute for a hotel can be extracted through preference learning only when sufficient sentiment information of that attribute is present. To ensure the reliability of training results, this study excludes attributes mentioned in online reviews with a frequency below 0.1, focusing on more prevalent attributes for analysis.

Table 3
Basic information about the online reviews of twenty hotels.

Hotel	Overall star rating	Number of reviews	Frequency of attributes mentioned in online reviews									
			Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H1	4.5	345	0.79	0.25	0.24	0.63	0.39	0.21	**0.04**	0.58	0.60	0.28
H2	4.0	887	0.77	0.54	0.24	0.48	0.71	0.16	**0.02**	0.71	0.19	**0.07**
H3	4.5	526	0.84	0.59	0.17	0.21	0.67	0.35	**0.04**	0.66	0.24	0.30
H4	4.0	590	0.68	0.71	0.31	0.56	0.78	0.12	**0.05**	0.74	0.32	**0.03**
H5	2.5	183	0.70	0.35	0.40	0.53	0.57	**0.09**	**0.07**	0.78	0.33	**0.01**
H6	4.0	622	0.69	0.75	0.22	0.43	0.76	0.13	**0.05**	0.79	0.22	**0.06**
H7	3.0	426	0.65	0.30	0.46	0.54	0.67	0.10	0.12	0.80	0.35	**0.03**
H8	3.5	271	0.70	0.75	0.38	0.51	0.82	**0.04**	0.11	0.75	0.24	**0.03**
H9	5.0	1593	0.89	0.47	0.12	0.19	0.68	0.24	**0.01**	0.67	0.21	0.27
H10	4.5	1742	0.85	0.59	0.15	0.17	0.59	0.39	**0.04**	0.70	0.21	0.37
H11	4.5	734	0.85	0.55	0.17	0.29	0.75	0.43	**0.05**	0.66	0.31	0.14
H12	4.0	998	0.78	0.36	0.19	0.16	0.46	0.39	**0.02**	0.66	0.24	0.46
H13	4.0	1508	0.77	0.76	0.33	0.53	0.81	**0.06**	0.12	0.71	0.25	**0.05**
H14	4.5	1149	0.85	0.48	0.19	0.12	0.54	0.19	**0.04**	0.61	0.32	0.27
H15	4.5	489	0.69	0.53	0.41	0.54	0.63	**0.04**	0.07	0.82	0.34	**0.01**
H16	4.5	581	0.84	0.50	0.19	0.14	0.55	0.40	**0.04**	0.63	0.26	0.28
H17	3.5	555	0.69	0.55	0.36	0.54	0.77	**0.04**	0.10	0.65	0.24	**0.00**
H18	3.5	369	0.71	0.41	0.39	0.53	0.77	**0.08**	**0.08**	0.82	0.30	**0.02**
H19	2.5	485	0.69	0.53	0.41	0.54	0.64	**0.05**	**0.07**	0.82	0.34	**0.01**
H20	4.0	1474	0.80	0.46	0.31	0.46	0.75	**0.09**	**0.06**	0.74	0.26	0.21
Average	4.0	776	0.76	0.52	0.28	0.41	0.67	0.18	**0.06**	0.72	0.29	0.15

Note. Bolded numbers indicate frequencies less than 0.1.

Table 4
The prediction ability of preference models estimated for each hotel.

	Mean	Min.	Max.		Mean	Min.	Max.
H1	0.974	0.962	0.986	H11	0.972	0.965	0.981
H2	0.954	0.937	0.967	H12	0.958	0.952	0.965
H3	0.976	0.969	0.983	H13	0.950	0.943	0.956
H4	0.949	0.936	0.963	H14	0.977	0.969	0.981
H5	0.947	0.929	0.967	H15	0.947	0.940	0.956
H6	0.958	0.949	0.968	H16	0.969	0.958	0.981
H7	0.947	0.933	0.959	H17	0.938	0.928	0.950
H8	0.955	0.942	0.966	H18	0.953	0.939	0.965
H9	0.986	0.980	0.990	H19	0.946	0.937	0.959
H10	0.979	0.975	0.983	H20	0.949	0.944	0.957

4.2. Estimating attribute importance

The online reviews of each hotel are organized into a dataset for preference learning analysis. Following the process of preference learning (Module I), we estimate the preference models for each hotel. The four parameters defined in Model 1 are set as $w = 0.05$ (it is greater than 0 because each of the considered attributes is important), $\delta_1 = \delta_2 = 0.01$ (a small positive value), and $\mu = 0.05$ (it is less than the average difference 0.2 in the four thresholds and greater than 0). We train each dataset 100times, and at this point, the "mean" preference model obtained from each dataset has reached stability. Table A.2 in the Appendix shows the confidence intervals (95% confidence level) of the reward and penalty indices of estimated attributes during the 100 training sessions for each hotel. Table 4 presents the mean, minimum, and maximum values of the prediction ability of the estimated preference models for each hotel.

Simulations are performed to illustrate the robustness of the learning results. We simulate each dataset 10,000 times. The fitting ability of each preference model generated for simulations is calculated by Eq. (11), and the mean, minimum, and maximum values of the fitting ability of the 10,000 preference models generated for simulations are determined, as shown in Table 5. The mean, minimum, and maximum values of the fitting ability of preference models estimated over 100 training sessions for each dataset are also presented in Table 5. By comparing the fitting ability of the preference models obtained by the training process and the simulation process, it is found that the robustness of the training results for five hotels, including H9, H10, H15, H18, and H19, is not high. That is to say, the "mean" preference model obtained by the 100 training sessions cannot accurately estimate the consumer satisfaction of these five hotels. Therefore, we use Eq. (13) to estimate the reward and penalty indices of attributes of these five hotels, and the results are shown in Table 6. The robustness of the training results for the other 15 hotels, including H1-H8, H11-H14, H16, H17, and H20, are high. The reward and penalty indices of attributes of these hotels are estimated by Eq. (12). The results are shown in Table A.2 in the Appendix.

4.3. Developing product improvement strategies

The estimated reward and penalty indices of attributes are used to identify the satisfaction factors of each hotel following the steps of Module II. The attribute performance of each hotel is estimated by Eq. (14). On these bases, we conduct asymmetric IPA to determine the categories of attributes for each hotel, and the results are shown in Table A.3 in the Appendix.

Based on the steps of Module III, we use the datasets of H15 and H17 as examples to illustrate how to allocate investments for attribute improvement. The hypothetical costs of improving the performance of each attribute by one unit for these two hotels are shown in Table 7. Suppose that the managers of H15 and H17 decide to increase or maintain their investments in each attribute with total investment $C = 0.3$ and $C = 0.2$, respectively. Using Model 2, the allocation of investments in attribute improvements of both hotels is determined to maximize consumer satisfaction, and the results are shown in Table 8. Through investment, the overall performance value of H15 can be improved from 0.410 (negative) to 0.504 (positive), while that of H17 can be improved from 0.493 (negative) to 0.571 (positive). The performance of attributes before and after investment for H15 and H17 is shown in Table 9.

Table 5
The fitting ability of preference models estimated in the learning process and simulation process.

Hotel	Learning			Simulation			Hotel	Learning			Simulation		
	Mean	Min.	Max.	Mean	Min.	Max.		Mean	Min.	Max.	Mean	Min.	Max.
H1	0.9744	0.9740	0.9748	0.9744	0.9737	0.9748	H11	0.9750	0.9728	0.9759	0.9741	0.9730	0.9749
H2	0.9580	0.9559	0.9593	0.9592	0.9588	0.9594	H12	0.9603	0.9589	0.9608	0.9606	0.9601	0.9610
H3	0.9790	0.9764	0.9801	0.9782	0.9765	0.9794	H13	0.9512	0.9504	0.9518	0.9518	0.9517	0.9518
H4	0.9541	0.9522	0.9553	0.9552	0.9547	0.9556	H14	0.9783	0.9765	0.9788	0.9789	0.9788	0.9790
H5	0.9538	0.9476	0.9564	0.9474	0.9455	0.9493	H15	0.9496	0.9462	0.9507	0.9445	0.9432	0.9458
H6	0.9612	0.9589	0.9620	0.9591	0.9576	0.9602	H16	0.9726	0.9694	0.9736	0.9710	0.9700	0.9718
H7	0.9520	0.9491	0.9535	0.9538	0.9536	0.9539	H17	0.9426	0.9392	0.9438	0.9394	0.9379	0.9406
H8	0.9612	0.9553	0.9630	0.9625	0.9617	0.9631	H18	0.9566	0.9514	0.9581	0.9476	0.9453	0.9499
H9	0.9864	0.9859	0.9866	0.9682	0.9671	0.9694	H19	0.9496	0.9506	0.9464	0.9446	0.9432	0.9457
H10	0.9798	0.9787	0.9801	0.9744	0.9737	0.9752	H20	0.9505	0.9493	0.9510	0.9501	0.9496	0.9504

Table 6
The reward and penalty indices of the hotels whose "mean" preference models are not representative.

Hotel		Serv ice	Food	Price	Clean liness	Loca tion	Deco ration	Inter net	Bed room	Bath room	Recr eation
H9	Reward	0.00	0.00	0.50	0.00	0.00	0.00	–	1.00	0.00	0.00
	Penalty	0.25	0.07	0.33	0.55	0.18	0.55	–	0.92	0.84	0.34
H10	Reward	0.90	1.00	0.68	0.06	0.28	0.35	–	0.98	0.80	0.71
	Penalty	0.61	0.39	0.96	0.93	0.64	0.15	–	0.92	0.10	0.36
H15	Reward	0.14	0.15	0.76	0.57	0.37	–	–	0.64	0.03	–
	Penalty	0.92	0.59	0.66	0.33	0.70	–	–	0.95	0.88	–
H18	Reward	0.73	0.27	0.29	0.26	0.37	–	–	0.07	0.54	–
	Penalty	0.59	0.79	0.87	0.62	0.86	–	–	0.84	0.69	–
H19	Reward	0.15	0.11	0.80	0.54	0.38	–	–	0.69	0.08	–
	Penalty	0.88	0.68	0.74	0.39	0.68	–	–	0.97	0.91	–

Table 7
The hypothetical costs of improving the performance of each attribute by one unit for H15 and H17.

Hotel	Serv ice	Food	Price	Clean liness	Loca tion	Deco ration	Inter net	Bedr oom	Bath room	Recr eation
H15	0.644	0.578	0.524	0.500	1.000	–	–	0.501	0.500	–
H17	0.521	0.534	0.675	0.455	0.936	–	0.431	0.545	0.568	–

Table 8
The allocation of investments in attribute improvements for H15 and H17.

Hotel	Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H15	0.041	0.000	0.002	0.039	0.000	–	–	0.158	0.060	–
H17	0.0252	0.075	0.000	0.083	0.000	–	0.017	0.000	0.000	–

Table 9
The performance of attributes before and after investment for H15 and H17.

Hotel		Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H15	Before	0.44	0.43	0.40	0.43	0.53	–	–	0.36	0.38	–
	After	0.50	0.43	0.40	0.50	0.53	–	–	0.68	0.50	–
H17	Before	0.55	0.52	0.50	0.51	0.56	–	0.46	0.41	0.43	–
	After	0.60	0.66	0.50	0.69	0.56	–	0.50	0.41	0.43	–

4.4. Discussions

This section discusses the experimental results and uses H15 (its "mean" preference model is not representative) and H17 (its "mean" preference model is representative) as examples for illustration.

(1) The results of preference learning.

Prediction and fitting ability are two measures of the reliability of preference learning results. As shown in Tables 4 and 5, the prediction ability of the estimated preference models for testing sets is close to their fitting ability for the whole dataset of each hotel. This illustrates that the learning process does not face the problem of overfitting and that the estimated preference models are effective for predicting hotel consumer satisfaction. In addition, the simulation results show that the average value of each preference parameter estimated for most hotels can construct a "mean" preference model that is representative. The reason for not being able to find a "mean" preference model with representativeness for the five hotels (H9, H10, H15, H18, and H19) may be that consumers' preferences for them vary significantly. For further clarification, we perform an additional 100 training sessions on the online reviews of these five hotels. The training results are the same as those obtained in the previous 100 estimations and still fail to construct a "mean" preference model with representativeness for each of these five hotels. It indicates that 100 training sessions are sufficient to find a "mean" preference model and obtain robust results.

(2) The results of sentiment analysis.

In Model 1, there are four parameters, including w, δ_1, δ_2 and μ, that need to be defined. We perform sensitivity analysis to capture these parameters' influence on results. We set $\delta_1 = \delta_2$ since they have similar meanings. In Sect. 4.2, we set $w = 0.05$, $\delta_1 = \delta_2 = 0.01$ and $\mu = 0.05$. For sensitivity analysis, we select 10 values close to the defined value for each parameter, that is, $w \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1\}$, $\delta_1 = \delta_2 \in \{0.002, 0.004, 0.006, 0.008, 0.01, 0.012, 0.014, 0.016, 0.018, 0.2\}$ and $\mu \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1\}$. When performing sensitivity analysis on one parameter, the values of other parameters are set as their initial values.

The average values of the reward and penalty indices for each attribute of H15 estimated using different parameters are shown in Figs. 2 and 3, respectively, and those of H17 are shown in Figs. 4 and 5, respectively. The prediction ability of the preference models estimated for H15 and H17 using different parameters is presented in Figs. 6 and 7, respectively. Overall, for both H15 and H17, the parameters δ_1 and δ_2 do not have significant effects on the prediction ability of preference models and the estimation accuracy of reward and penalty indices. As can be seen from Figs. 3–6, the parameter w (the minimum attribute weight) has a certain influence on learning results, and the larger the minimum weight is, the larger the estimated reward and penalty indices are. Therefore, analysts should be cautious in setting this parameter. In addition, as can be seen from Fig. 7, the parameter μ (the minimum difference between adjacent thresholds that define the lower and upper limits of each star rating) has a significant effect on the prediction ability of preference models estimated for H15, and the larger μ is, the less prediction ability the preference models have. Therefore, this parameter should be

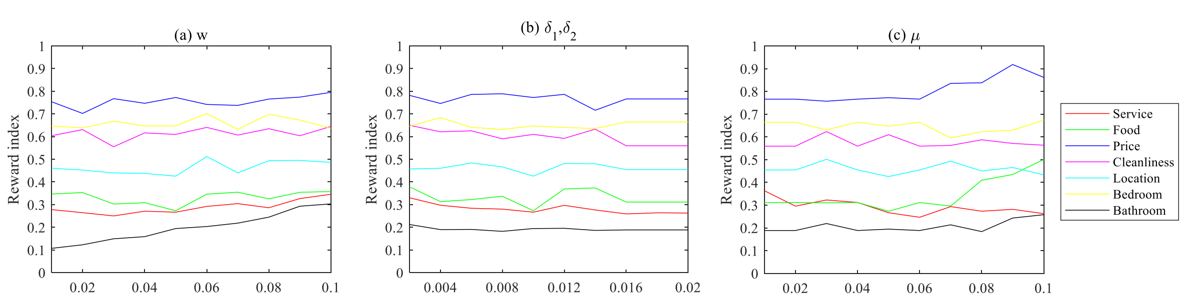

Fig. 2. The average values of the reward indices of H15 estimated using different parameters.

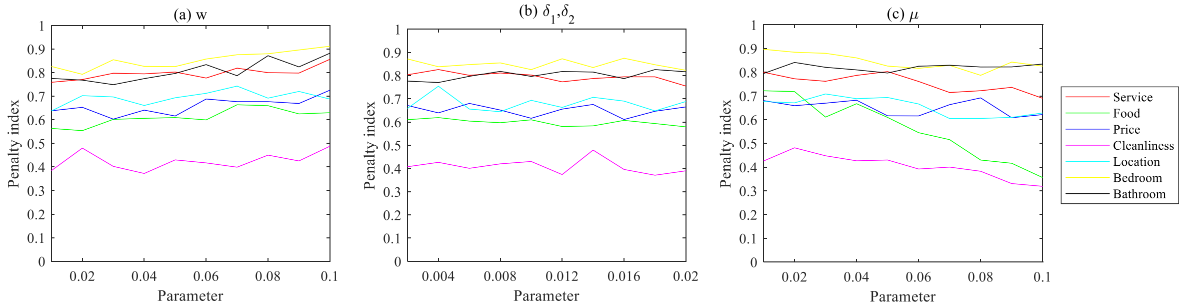

Fig. 3. The average values of the penalty indices of H15 estimated using different parameters.

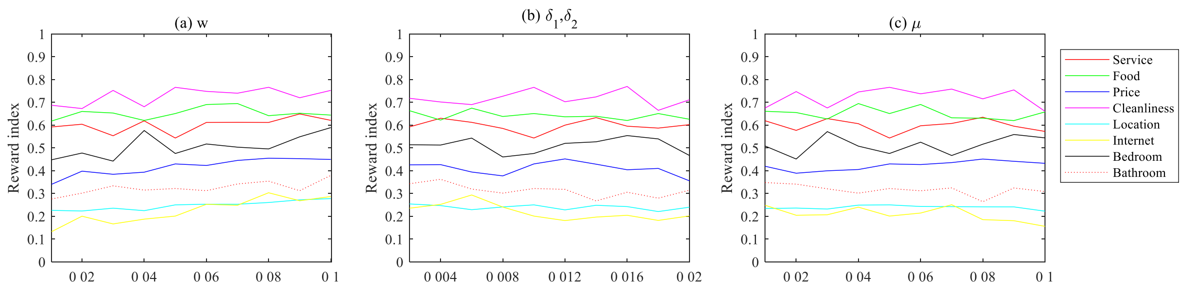

Fig. 4. The average values of the reward indices of H17 estimated using different parameters.

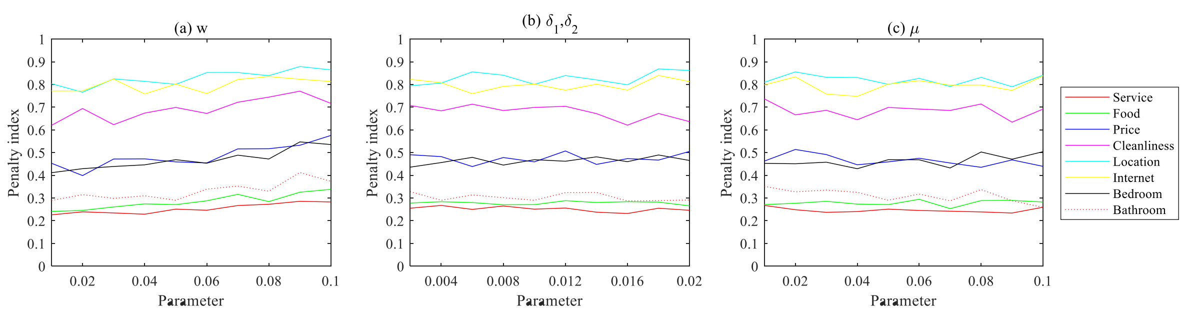

Fig. 5. The average values of the penalty indices of H17 estimated using different parameters.

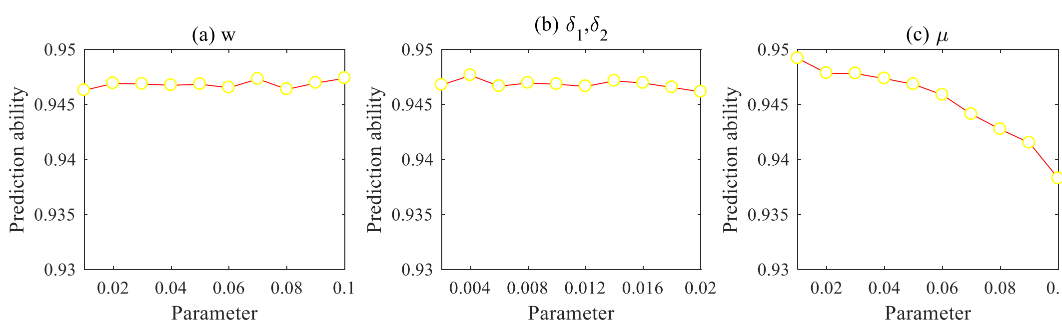

Fig. 6. The prediction ability of preference models estimated for H15 using different parameters.

set to a small value when modeling preferences for this hotel based on online reviews.

(3) The results of attribute importance.

As can be seen from Table A.2 in the Appendix, the importance of an attribute varies for different hotels. We take H15 and H17 as examples for detailed analysis. When attribute performance is positive, the ranking of the attributes of H15 in terms of importance is: "price" ≻ "bedroom" ≻ "cleanliness" ≻ "location" ≻ "food" ∼ "service" ≻ "bathroom", in which "price", "bedroom" and "cleanliness" play a key role in enhancing consumer satisfaction with this hotel, and that of H17 is: "cleanliness" ≻ "food" ≻ "service" ≻ "bedroom" ≻ "price" ≻ "bathroom" ≻ "location" ≻ "Internet", in which "cleanliness", "food" and "service" play a key role in enhancing consumer satisfaction with this hotel. When attribute performance is negative, for H15, the ranking of attributes is: "bedroom" ≻ "service" ≻ "bathroom" ∼ "location" ≻ "price" ≻ "food" ≻ "cleanliness", in which all attributes other than "cleanliness" have a significant impact on improving consumer satisfaction with this hotel, and for H17, the ranking is: "location" ∼ "Internet" ≻ "cleanliness" ≻ "bedroom"

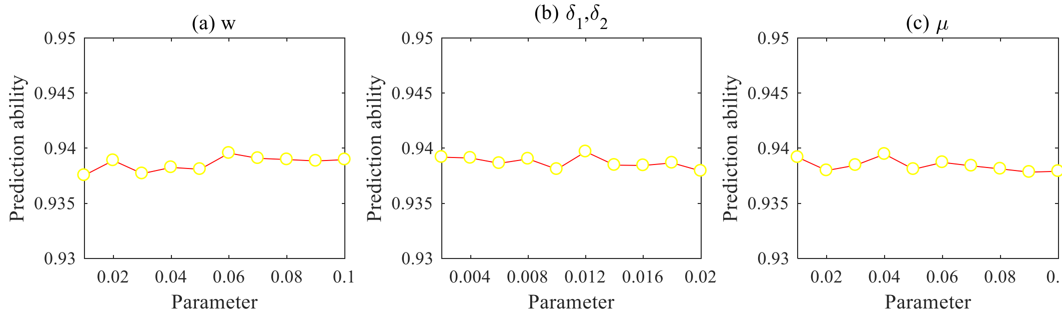

Fig. 7. The prediction ability of preference models estimated for H17 using different parameters.

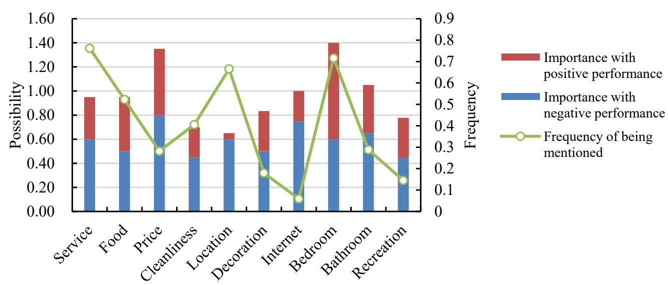

Fig. 8. The possibility of each attribute being important in terms of twenty hotels.

≻ "price" ≻ "bathroom" ≻ "food" ≻ "service", in which "location", "Internet" and "cleanliness" have a significant impact on improving consumer satisfaction with this hotel.

To capture the overall picture of the importance of each attribute, a statistical analysis is conducted for twenty hotels. We calculate the possibility of each attribute being important, specifically, the ratio of the number of hotels with an average reward (or penalty) index greater than or equal to 0.5 for an attribute to the number of all hotels involved in that attribute. The results are shown in Fig. 8. Considering both reward and penalty indices, "bedroom" and "price" are the two most important attributes. In general, each attribute has a great impact on consumer satisfaction when their performance is negative. However, when attribute performance is positive, there is a large variation in attribute importance, with some attributes (such as "bedroom" and "price") having a significant impact on enhancing consumer satisfaction and some attributes (such as "location", "cleanliness" and "Internet") not. This result can be explained by the risk-averse psychology of consumers. Most consumers tend to buy products that meet the minimum tolerance for each attribute, and therefore pay more attention to the poorly performing attributes when measuring the performance of a product.

(4) The results of attribute prioritization.

As can be seen from Table A.3 in the Appendix, the satisfaction factor to which an attribute belongs varies from one hotel to another. The asymmetric IPA plots of H15 and H17 are shown in Fig. 9. For H15, "service", "food", "location" and "bathroom" are must-be factors, "price" and "bedroom" are performance factors, and "cleanliness" is an excitement factor. For H17, "location" and "Internet" are must-be factors, "cleanliness" is a performance factor, "service" and "food" are excitement factors, and "price", "bedroom" and "bathroom" are indifferent factors. Except for "location", the performance of all the other attributes of H15 is negative, and most of them are must-be factors or performance factors. Therefore, the hotel H15 should improve these attributes. However, limited resources usually cannot support all attributes to be improved. The proposed optimization model allows for a rational allocation (see Table 8) of investments to attributes to achieve maximum consumer satisfaction. Assuming that the investments are equally allocated to all attributes, the consumer satisfaction degree of H15 will be 0.491, which is smaller than the optimal objective value obtained by Model 2. As for H17, the

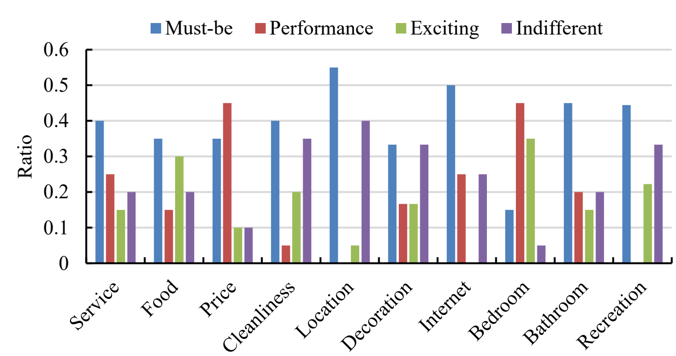

Fig. 10. The ratios at which each attribute is classified as one of four satisfaction factors.

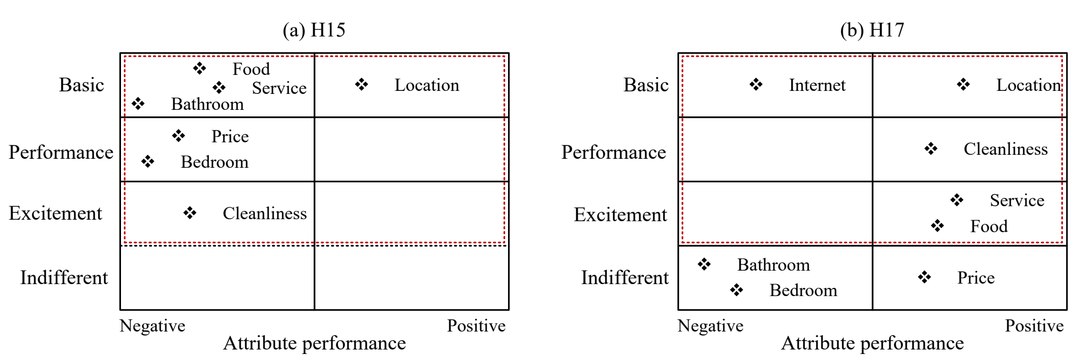

Fig. 9. The asymmetric IPA plots of H15 and H17.

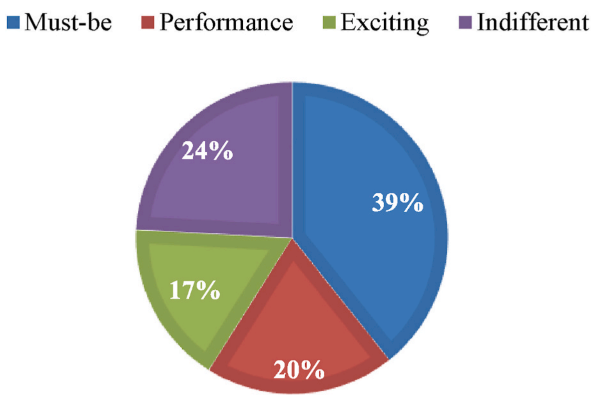

Fig. 11. The rate at which attributes are classified into each of four satisfaction factors across twenty hotels.

performance of “Internet”, “bedroom”, and “bathroom” is negative, while the last two attributes are indifferent factors. Therefore, investments should be used to improve “Internet” first. However, how to allocate the remaining investments after improving the “Internet” remains a challenge. In this regard, our proposed method for optimal allocation of investments is useful for improving consumer satisfaction.

To capture the classification of each attribute for satisfaction factors, we conduct statistical analysis for twenty hotels. The ratios of each attribute classified as a must-be factor, performance factor, excitement factor, and indifferent factor are shown in Fig. 10. Generally, “service” is a must-be factor as well as “Internet”, “bathroom” and “recreation”, “food” is a must-be or excitement factor, “price” is a performance or must-be factor, “cleanliness” is a must-be or indifferent factor as well as “location” and “decoration”, and “bedroom” is a performance or excitement factor. We also calculate the rate at which attributes are classified into each of the four satisfaction factors across twenty hotels. As shown in Fig. 11, most attributes (39%) are must-be factors, while the least attributes (17%) are excitement factors. Hotel managers should make performance or must-be factors (e.g., “bedroom”, “service”, “Internet”, “bathroom”, and “recreation”) perform as well as possible to meet consumer expectation, and characterize excitement factors (e.g., “food”) to make them attractive to consumers.

5. Research implications

The contributions of this study are three-fold. First, it contributes to multiple attribute decision-making (MADM) fields. Preference learning is an important branch of MADM, which refers to learning preference models through historical decision examples. The additive value function is one of the most frequently used preference models in preference learning. It has two assumptions that the importance of each attribute is a constant and the same set of attributes are considered for different decision examples. In many application areas, such as consumer preference analysis, these two assumptions are not satisfied. On the one hand, the three-factor theory states that consumers’ preferences for attributes are affected by attributes’ performance. In this study, we introduced reward and penalty indices into the additive value function to characterize the importance of attributes when they perform positively and negatively, respectively. On the other hand, to resolve the problem where different consumers value different attributes of a product, a dummy variable is added to the additive value function, and then the assumption that the same set of attributes must be considered for all decision examples is eliminated. For the issue regarding large-scale decision examples, we proposed a simulation method to verify the robustness of learning results, thus improving the reliability of the results.

Second, our research contributes to consumer preference analysis based on online reviews. At a narrow level, consumer preference refers to the degree to which consumers prefer a product or product mix. According to the MAVT, consumer preference for a product can be measured by the preferences of a consumer for different attributes such that the more important an attribute is, the more the product’s performance on that attribute can influence the consumer’s satisfaction. A consumer’s preferences for attributes can be extracted from online reviews. The overall star rating of a product can be considered as an aggregation of the ratings of different attributes. Scholars have estimated attribute importance based on the relationship between the overall rating and the ratings of attributes through machine learning methods (Bi et al., 2019). Since most consumers mention only a few product attributes in their online reviews, the performance of these models is largely affected by the data sparsity problem caused by the large number of missing ratings. In this paper, a preference learning model based on an asymmetric value function was used to extract consumer preference models from online reviews, which avoided the data sparsity problem. The proposed approach also has an advantage in terms of interpretability since the underlying preference model has a solid theoretical foundation, *i.e.*, the MAVT. The method can be applied not only to attribute improvement which is the focus of this paper but also to product recommendations based on consumers’ personalized preference models learned from online reviews.

Third, the study contributes to the literature on consumer satisfaction analysis by conducting asymmetric IPA based on online reviews. (1) Attributes are classified into eight categories based on their performance and importance. This classification provides managers with more detailed strategies for attribute improvement than the classification with four categories defined in the traditional IPA. (2) The proposed optimization model can determine a specific allocation strategy for investment in attributes, to maximize consumer satisfaction with limited resources. (3) In the experimental study, by implementing the asymmetric IPA on twenty hotels, it was found that the satisfaction factor to which an attribute belongs varies from hotel to hotel, and investments in attributes need to be integrated considering attribute importance, attribute performance, and costs.

6. Conclusions

We developed a methodology for conducting asymmetric IPA through a preference learning process based on online reviews. Based on the MAVT, a preference model was constructed by an asymmetric value function to portray the relationship among attribute performance, attribute importance, and consumer satisfaction. To characterize the asymmetric effect of attribute performance on consumer satisfaction, we improved the additive value function by introducing a reward index and a penalty index to represent the importance of an attribute when its performance is positive and negative, respectively. We also introduced a dummy variable into the value function to depict whether an online review contains the sentiment information of an attribute, to solve the data sparsity issue of online reviews. A preference learning model was constructed to estimate reward and penalty indices defined in the preference model. In addition, simulations were designed to measure the robustness of preference learning results. To provide managers with specific investment strategies for product improvement, we not only constructed a classification method for attributes through the asymmetric IPA but also proposed an optimization model to allocate investments to maximize consumer satisfaction. Through a case study, we proved that the proposed method can give corporate managers inspiration on cost and performance to improve consumer satisfaction.

Through the analysis of hotel online reviews, we gained the following inspirations: (1) without financial constraints, hotel managers can prioritize optimizing must-be factors (e.g., service, Internet, bathroom, recreation) with negative performance and performance factors (e.g., bedroom and price) to meet consumer expectations, while also differentiating with excitement factors (e.g., food) to enhance appeal; (2) within financial constraints, hotel managers can allocate investments to each attribute through an optimization model considering their factors, importance, and performance. This model, unlike a uniform, equal-investment strategy for attributes within the same category (e.g., must-be factors with negative performance or performance factors), ensures a more precise allocation of investments to maximize consumer satisfaction under budget limits.

There are unsolved issues that can be addressed in the future. First, the proposed methodology was used for consumer satisfaction analysis on products that contain a large number of online reviews. For products that do not have online reviews, the consumer satisfaction analysis needs to be conducted with survey data. In this case, the preference learning model can be used to process survey data, which does not require respondents to directly judge the importance of attributes as the traditional IPA does but only to provide their attribute-level satisfaction and overall satisfaction with products. To enrich the data scale, a cross-platform strategy can be implemented, integrating reviews across multiple online sources for a broader asymmetric IPA. In addition, the proposed preference model assumed that the relationship between attribute importance and performance is represented discretely based on reward and penalty indices. Future research should consider a continuous function to portray their relationship because human cognition is usually continuous. Finally, the proposed optimization model used to allocate investments considered only the impact of costs and attribute importance and performance in the allocation. Future research should consider more constraints, such as the technical difficulty and the time of improvement.

CRediT authorship contribution statement

Xingli Wu: Writing – original draft, Visualization, Validation, Methodology, Investigation. **Huchang Liao:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

No conflict of interest exits in the submission of this manuscript.

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Appendix

Table A.1
Attributes and keywords of hotels for consumer satisfaction analysis

Attribute	Keyword
Service	Service/hospitality/reception/smile/staff/manager/waiter/host/check-in/Sri/job/effort/low/employees/employee/working/help/person/helpful/hosts/friendly/waiter/woman/gentleman/lady/receptionist
Food	Cereal/juice/fruit/egg/toast/pastries/bagel/caffe/drink/wine/breakfast/food/lunch/meal/drinks/tea/vending machines/coffee machine
Price	Cost/deal/expense/price/value/pay/money/expensive/overpriced/costs/charging/charge/paid/smelt/cleaned/cleanest/prices
Cleanliness	Clean/cleanliness/freshness/neatness/dirtiness/dirty/stain/broken/mold/peel/dust/fresh/smell/spotless
Location	Location/distance/central/located/close/easy to find/hard to find/position/far from
Decoration	Decoration/boutique/design/style/hip/modern/chic/atmosphere/decorations/decorated/designed
Internet	Internet/WiFi/computer/print/wireless/TV/software/Wi-Fi/wifi
Bedroom	Room/lamp/electric/shelf/outlet/bedside/rack/drawer/bedroom/sofa/beacon/bug/bite/bedbug/sheet/mattress/blanket/iron/safe/sleep/bed/awaken/slept/beds/AC/air conditioner
Bathroom	Bathroom/marble/robe/plush/tub/soft/bathrobe/screen/shampoo/soap/bathroom/bath/bathrooms/showers/shower/toilets
Recreation	Recreation/rooftop/pool/lounge/music/bar/terrace/bartend/Christmas/lounge/games

Table A.2
The confidence intervals of attribute importance estimated for each hotel

		Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H1	Reward	0.40 ± 0.03	0.79 ± 0.05	0.72 ± 0.05	0.39 ± 0.04	0.09 ± 0.02	0.33 ± 0.05	–	0.74 ± 0.05	0.30 ± 0.05	0.46 ± 0.06
	Penalty	0.58 ± 0.05	0.25 ± 0.04	0.65 ± 0.04	0.75 ± 0.06	0.59 ± 0.05	0.13 ± 0.04	–	0.43 ± 0.03	0.31 ± 0.04	0.81 ± 0.05
H2	Reward	0.27 ± 0.03	0.36 ± 0.04	0.71 ± 0.07	0.31 ± 0.04	0.22 ± 0.03	0.16 ± 0.03	–	0.81 ± 0.05	0.31 ± 0.07	–
	Penalty	0.79 ± 0.05	0.36 ± 0.05	0.25 ± 0.06	0.08 ± 0.01	0.43 ± 0.05	0.42 ± 0.09	–	0.41 ± 0.04	0.71 ± 0.05	–
H3	Reward	0.24 ± 0.03	0.14 ± 0.02	1.00 ± 0.00	0.09 ± 0.02	0.13 ± 0.02	0.19 ± 0.02	–	0.33 ± 0.05	0.11 ± 0.02	0.23 ± 0.03
	Penalty	0.69 ± 0.05	0.63 ± 0.05	0.79 ± 0.04	0.38 ± 0.07	0.48 ± 0.05	0.36 ± 0.06	–	0.76 ± 0.04	0.42 ± 0.05	0.26 ± 0.04
H4	Reward	0.11 ± 0.02	0.53 ± 0.05	0.11 ± 0.03	0.17 ± 0.03	0.42 ± 0.04	0.81 ± 0.06	–	0.54 ± 0.06	0.69 ± 0.05	–
	Penalty	0.56 ± 0.05	0.50 ± 0.05	0.87 ± 0.04	0.46 ± 0.06	0.64 ± 0.04	0.54 ± 0.07	–	0.36 ± 0.04	0.59 ± 0.05	–
H5	Reward	0.44 ± 0.05	0.27 ± 0.04	0.68 ± 0.06	0.37 ± 0.06	0.21 ± 0.02	–	–	0.80 ± 0.05	0.16 ± 0.01	–
	Penalty	0.78 ± 0.04	0.24 ± 0.03	0.97 ± 0.02	0.22 ± 0.04	0.22 ± 0.03	–	–	0.46 ± 0.03	0.52 ± 0.05	–
H6	Reward	0.40 ± 0.03	0.42 ± 0.03	0.55 ± 0.06	0.61 ± 0.05	0.58 ± 0.03	0.49 ± 0.05	–	0.95 ± 0.02	0.60 ± 0.05	–
	Penalty	0.44 ± 0.04	0.27 ± 0.04	0.86 ± 0.04	0.33 ± 0.04	0.42 ± 0.04	0.57 ± 0.07	–	0.55 ± 0.04	0.59 ± 0.06	–
H7	Reward	0.18 ± 0.02	0.61 ± 0.07	0.16 ± 0.04	0.19 ± 0.03	0.13 ± 0.01	0.65 ± 0.07	0.34 ± 0.07	0.56 ± 0.07	0.33 ± 0.06	–
	Penalty	0.32 ± 0.03	0.35 ± 0.05	0.36 ± 0.05	0.52 ± 0.05	0.27 ± 0.03	0.46 ± 0.07	0.87 ± 0.05	0.48 ± 0.04	0.30 ± 0.04	–
H8	Reward	0.10 ± 0.02	0.29 ± 0.03	0.21 ± 0.05	0.30 ± 0.02	0.06 ± 0.01	–	0.11 ± 0.02	0.93 ± 0.04	0.80 ± 0.06	–
	Penalty	0.27 ± 0.05	0.77 ± 0.04	0.79 ± 0.05	0.18 ± 0.04	0.30 ± 0.03	–	0.38 ± 0.06	0.63 ± 0.05	0.69 ± 0.07	–
H9	Reward	0.19 ± 0.01	0.12 ± 0.01	0.55 ± 0.07	0.11 ± 0.01	0.13 ± 0.01	0.19 ± 0.01	–	1.00 ± 0.00	0.12 ± 0.01	0.19 ± 0.01
	Penalty	0.44 ± 0.02	0.38 ± 0.02	0.47 ± 0.03	0.60 ± 0.05	0.43 ± 0.03	0.61 ± 0.04	–	0.84 ± 0.04	0.78 ± 0.04	0.47 ± 0.03
H10	Reward	0.68 ± 0.03	0.92 ± 0.02	0.63 ± 0.05	0.16 ± 0.03	0.46 ± 0.02	0.48 ± 0.02	–	0.85 ± 0.03	0.65 ± 0.04	0.60 ± 0.03
	Penalty	0.59 ± 0.04	0.43 ± 0.03	0.88 ± 0.03	0.84 ± 0.04	0.59 ± 0.05	0.32 ± 0.03	–	0.73 ± 0.03	0.27 ± 0.03	0.43 ± 0.04

(*continued on next page*)

Table A.2 (*continued*)

		Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H11	Reward	0.62 ± 0.04	0.63 ± 0.04	0.58 ± 0.05	0.33 ± 0.04	0.42 ± 0.03	0.87 ± 0.03	–	0.85 ± 0.04	0.59 ± 0.04	0.50 ± 0.08
	Penalty	0.49 ± 0.05	0.28 ± 0.03	0.77 ± 0.05	0.17 ± 0.04	0.50 ± 0.05	0.24 ± 0.04	–	0.80 ± 0.04	0.23 ± 0.04	0.62 ± 0.06
H12	Reward	0.37 ± 0.03	0.34 ± 0.03	0.38 ± 0.06	0.33 ± 0.04	0.14 ± 0.01	0.25 ± 0.02	–	0.97 ± 0.02	0.28 ± 0.04	0.39 ± 0.03
	Penalty	0.55 ± 0.03	0.58 ± 0.03	0.94 ± 0.02	0.67 ± 0.05	0.54 ± 0.03	0.65 ± 0.05	–	0.38 ± 0.03	0.68 ± 0.04	0.16 ± 0.02
H13	Reward	0.39 ± 0.03	0.41 ± 0.04	0.17 ± 0.03	0.46 ± 0.04	0.22 ± 0.02	–	0.95 ± 0.03	0.63 ± 0.05	0.28 ± 0.05	–
	Penalty	0.41 ± 0.03	0.56 ± 0.03	0.72 ± 0.04	0.19 ± 0.02	0.61 ± 0.02	–	0.73 ± 0.05	0.94 ± 0.02	0.51 ± 0.04	–
H14	Reward	0.78 ± 0.04	0.78 ± 0.04	0.55 ± 0.05	0.48 ± 0.06	0.47 ± 0.03	0.45 ± 0.04	–	0.79 ± 0.04	0.83 ± 0.03	0.58 ± 0.04
	Penalty	0.52 ± 0.04	0.47 ± 0.03	0.93 ± 0.03	0.58 ± 0.06	0.56 ± 0.04	0.57 ± 0.04	–	0.45 ± 0.03	0.43 ± 0.04	0.45 ± 0.04
H15	Reward	0.27 ± 0.04	0.27 ± 0.04	0.77 ± 0.06	0.61 ± 0.06	0.43 ± 0.04	–	–	0.65 ± 0.06	0.19 ± 0.03	–
	Penalty	0.80 ± 0.04	0.61 ± 0.05	0.62 ± 0.04	0.43 ± 0.04	0.69 ± 0.06	–	–	0.83 ± 0.03	0.80 ± 0.04	–
H16	Reward	0.65 ± 0.04	0.88 ± 0.03	0.18 ± 0.03	0.50 ± 0.06	0.47 ± 0.04	0.76 ± 0.04	–	0.47 ± 0.04	0.16 ± 0.04	0.11 ± 0.01
	Penalty	0.42 ± 0.03	0.50 ± 0.04	0.70 ± 0.05	0.07 ± 0.02	0.39 ± 0.04	0.68 ± 0.05	–	0.90 ± 0.03	0.66 ± 0.04	0.72 ± 0.06
H17	Reward	0.54 ± 0.05	0.65 ± 0.06	0.43 ± 0.06	0.77 ± 0.05	0.25 ± 0.02	–	0.20 ± 0.04	0.48 ± 0.07	0.32 ± 0.05	–
	Penalty	0.25 ± 0.03	0.27 ± 0.02	0.46 ± 0.06	0.70 ± 0.05	0.80 ± 0.04	–	0.80 ± 0.05	0.47 ± 0.04	0.29 ± 0.06	–
H18	Reward	0.74 ± 0.06	0.38 ± 0.05	0.40 ± 0.05	0.39 ± 0.05	0.45 ± 0.05	–	–	0.27 ± 0.03	0.59 ± 0.07	–
	Penalty	0.55 ± 0.04	0.76 ± 0.05	0.73 ± 0.04	0.59 ± 0.06	0.80 ± 0.04	–	–	0.74 ± 0.04	0.69 ± 0.06	–
H19	Reward	0.28 ± 0.04	0.25 ± 0.04	0.79 ± 0.06	0.56 ± 0.06	0.46 ± 0.04	–	–	0.65 ± 0.06	0.21 ± 0.04	–
	Penalty	0.76 ± 0.04	0.59 ± 0.04	0.65 ± 0.04	0.45 ± 0.04	0.67 ± 0.06	–	–	0.85 ± 0.03	0.8 ± 0.04	–
H20	Reward	0.82 ± 0.04	0.64 ± 0.04	0.20 ± 0.03	0.30 ± 0.03	0.48 ± 0.03	–	–	0.94 ± 0.02	0.94 ± 0.02	0.36 ± 0.05
	Penalty	0.51 ± 0.03	0.78 ± 0.04	0.90 ± 0.02	0.64 ± 0.04	0.84 ± 0.03	–	–	0.85 ± 0.03	0.68 ± 0.03	0.53 ± 0.04

Note. In each data, the left side of "±" is the average and the right side is half the length of the confidence interval.

Table A.3
The categories of attributes that have priority in improvement for each hotel

	Service	Food	Price	Cleanliness	Location	Decoration	Internet	Bedroom	Bathroom	Recreation
H1	Must-be	Excitement	Performance	Must-be	Must-be	Indifferent	–	Excitement	Indifferent	Must-be
	Q1	Q5	Q3	Q1	Q1	Q7	–	Q5	Q7	Q1
H2	Must-be	Indifferent	Excitement	Indifferent	Indifferent	Indifferent	–	Excitement	Must-be	–
	Q1	Q7	Q6	Q7	Q7	Q7	–	Q6	Q1	–
H3	Must-be	Must-be	Performance	Indifferent	Indifferent	Indifferent	–	Must-be	Indifferent	Indifferent
	Q1	Q1	Q4	Q7	Q7	Q7	–	Q1	Q7	Q7
H4	Must-be	Performance	Must-be	Indifferent	Must-be	Performance	–	Excitement	Performance	–
	Q1	Q2	Q2	Q7	Q1	Q3	–	Q6	Q3	–
H5	Must-be	Indifferent	Performance	Indifferent	Indifferent	–	–	Excitement	Must-be	–
	Q2	Q8	Q4	Q8	Q7	–	–	Q6	Q2	–
H6	Indifferent	Indifferent	Performance	Excitement	Excitement	Must-be	–	Performance	Performance	–
	Q7	Q7	Q3	Q5	Q5	Q1	–	Q4	Q4	–
H7	Indifferent	Excitement	Indifferent	Must-be	Indifferent	Excitement	Must-be	Excitement	Indifferent	–
	Q8	Q6	Q8	Q2	Q7	Q5	Q2	Q6	Q8	–
H8	Indifferent	Must-be	Must-be	Indifferent	Indifferent	–	Indifferent	Performance	Performance	–
	Q7	Q1	Q2	Q7	Q7	–	Q8	Q4	Q4	–
H9	Indifferent	Indifferent	Excitement	Must-be	Indifferent	Must-be	–	Performance	Must-be	Indifferent
	Q7	Q7	Q5	Q1	Q7	Q1	–	Q3	Q1	Q7
H10	Performance	Excitement	Performance	Must-be	Must-be	indifference	–	Performance	Excitement	Excitement
	Q3	Q5	Q4	Q1	Q1	Q7	–	Q3	Q5	Q5
H11	Excitement	Excitement	Performance	Indifferent	Indifferent	Excitement	–	Performance	Excitement	Must-be
	Q5	Q5	Q3	Q7	Q7	Q5	–	Q3	Q5	Q1
H12	Must-be	Must-be	Must-be	Must-be	Must-be	Must-be	–	Excitement	Must-be	Indifferent
	Q1	Q1	Q2	Q1	Q1	Q1	–	Q6	Q2	Q7
H13	Indifferent	Must-be	Must-be	Indifferent	Must-be	–	Performance	Performance	Must-be	–
	Q7	Q1	Q2	Q7	Q1	–	Q4	Q4	Q2	–
H14	Performance	Excitement	Performance	Must-be	Must-be	Must-be	–	Excitement	Excitement	Excitement
	Q3	Q5	Q4	Q1	Q1	Q1	–	Q5	Q5	Q5
H15	Must-be	Must-be	Performance	Excitement	Must-be	–	–	Performance	Must-be	–
	Q2	Q2	Q4	Q6	Q1	–	–	Q4	Q2	–
H16	Excitement	Performance	Must-be	Excitement	Indifferent	Performance	–	Must-be	Must-be	Must-be
	Q5	Q3	Q1	Q5	Q7	Q3	–	Q1	Q2	Q1
H17	Excitement	Excitement	Indifferent	Performance	Must-be	–	Must-be	Indifferent	Indifferent	–
	Q5	Q5	Q7	Q3	Q1	–	Q2	Q8	Q8	–
H18	Performance	Must-be	Must-be	Must-be	Must-be	–	–	Must-be	Performance	–
	Q3	Q2	Q2	Q1	Q1	–	–	Q2	Q4	–
H19	Must-be	Must-be	Performance	Excitement	Must-be	–	–	Performance	Must-be	–
	Q2	Q2	Q4	Q6	Q1	–	–	Q4	Q2	–
H20	Performance	Performance	Must-be	Must-be	Must-be	–	–	Performance	Must-be	Must-be
	Q3	Q3	Q2	Q1	Q1	–	–	Q4	Q2	Q1

Data availability

Data will be made available on request.

References

Albayrak, T., 2015. Importance performance competitor analysis (IPCA): a study of hospitality companies. Int. J. Hospit. Manag. 48, 135–142.

Alvarez, P.A., Ishizaka, A., Martínez, L., 2021. Multiple-criteria decision-making sorting methods: a survey. Expert Syst. Appl. 183. https://doi.org/10.1016/j.eswa.2021.115368.

Bi, J.W., Liu, Y., Fan, Z.P., Zhang, J., 2019. Wisdom of crowds: conducting importance-performance analysis (IPA) through online reviews. Tourism Manag. 70, 460–478.

Borgers, A., Vosters, C., 2011. Assessing preferences for mega shopping centres: a conjoint measurement approach. J. Retailing Consum. Serv. 18 (4), 322–332.

Cao, J., Hao, Z.S., Yang, J.W., Yin, J.B., Huang, X.Y., 2020. Prioritizing neighborhood attributes to enhance neighborhood satisfaction: an impact asymmetry analysis. Cities 105. https://doi.org/10.1016/j.cities.2020.102854.

Cheng, M.M., Jin, X., 2019. What do Airbnb users care about? An analysis of online review comments. Int. J. Hospit. Manag. 76, 58–70.

Dueñas, X., Rodríguez, M., Pérez, L.M., 2021. Asymmetric importance-performance analysis: measuring classification changes of destination attributes into basic, performance and excitement factors according to the segmentation criterion. Tourism Hospit. Res. 21 (4), 418–425.

Dyer, J.S., Smith, J.E., 2021. Innovations in the science and practice of decision analysis: the role of management science. Manag. Sci. 67 (9), 5301–5967.

Gehrlein, J., Miebs, G., Brunelli, M., Kadziński, M., 2023. An active preference learning approach to aid the selection of validators in blockchain environments. Omega 118. https://doi.org/10.1016/j.omega.2023.102869.

Hu, F., Li, H.X., Liu, Y., Teichert, T., 2020. Optimizing service offerings using asymmetric impact-sentiment-performance analysis. Int. J. Hospit. Manag. 89, 102557. https://doi.org/10.1016/j.ijhm.2020.102557.

Hu, N., Zhang, T., Gao, B.J., Bose, I., 2019. What do hotel customers complain about? Text analysis using structural topic model. Tourism Manag. 72, 417–426.

Lai, I.K.W., Hitchcock, M., 2016. A comparison of service quality attributes for stand-alone and resort-based luxury hotels in Macau: 3-Dimensional importance-performance analysis. Tourism Manag. 55, 139–159.

Li, C., Agyeiwaah, E., 2023. Online learning attributes on overall tourism and hospitality education learning satisfaction: tourism Agenda 2030. Tourism Rev. 78 (2), 395–410.

Li, Z., Stamolampros, P., Zhao, X.F., 2024. Dynamics in the asymmetric effects of job attributes on employee satisfaction: a mixed-method approach using big data. Tourism Manag. 105, 104967. https://doi.org/10.1016/j.tourman.2024.104967.

Liu, J.P., Kadziński, M., Liao, X.W., 2023. Modeling contingent decision behavior: a Bayesian nonparametric preference-learning approach. Inf. J. Comput. 35 (4), 764–785.

Liu, Y., Shi, J.L., Huang, F., Hou, J.R., Zhang, C.Z., 2024a. Unveiling consumer preferences in automotive reviews through aspect-based opinion generation. J. Retailing Consum. Serv. 77. https://doi.org/10.1016/j.jretconser.2023.103605.

Liu, X., Zhang, N., Hao, X.L., 2024b. A strategic model for service-oriented enterprises based on online reviews: the research of budget hotel chains in China. Inf. Technol. Manag. 1–18. https://doi.org/10.1007/s10799-024-00417-2.

Lu, L., Xu, P., Wang, Y.Y., Wang, Y., 2023. Measuring service quality with text analytics: considering both importance and performance of consumer opinions on social and non-social online platforms. J. Bus. Res. 169, 114298.

Martyn, K., Kadziński, M., 2023. Deep preference learning for multiple criteria decision analysis. Eur. J. Oper. Res. 305 (2), 781–805.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S., Dean, J., 2013. Distributed representations of words and phrases and their compositionality. Adv. Neural Inf. Process. Syst. 26, 3111–3119.

Pan, M.Q., Li, N., Law, R., Huang, X.K., Wong, I.A., Zhang, B.R., Li, L.Y., 2023. Service attribute prioritization based on the marginal utility of attribute performance. Int. J. Hospit. Manag. 114, 103560. https://doi.org/10.1016/j.ijhm.2023.103560.

Pratt, S., Suntikul, W., Agyeiwaah, E., 2020. Determining the attributes of gastronomic tourism experience: Applying impact-range performance and asymmetry analyses. Int. J. Tourism Res. 22 (5), 564–581.

Qahri-Saremi, H., Montazemi, A.R., 2023. Negativity bias in the diagnosticity of online review content: the effects of consumers' prior experience and need for cognition. Eur. J. Inf. Syst. 32 (4), 717–734.

Shin, J., Joung, J., Lim, C., 2024. Determining directions of service quality management using online review mining with interpretable machine learning. Int. J. Hospit. Manag. 118, 103684. https://doi.org/10.1016/j.ijhm.2023.103684.

Song, Y., Xiu, Y.F., Zhou, L.P., Wang, J.Y., 2024. Implementing multi-attribute utility theory in service recovery: an operational management perspective on online retailing. J. Retailing Consum. Serv. 81. https://doi.org/10.1016/j.jretconser.2024.103968.

Sun, S., Fang, D.W., Cao, J., 2020. Exploring the asymmetric influences of stop attributes on rider satisfaction with bus stops. Travel Behav. Soc. 19, 162–169.

Tuan, V.A., Van Truong, N., Tetsuo, S., An, N.N., 2022. Public transport service quality: policy prioritization strategy in the importance-performance analysis and the three-factor theory frameworks. Transport. Res. Pol. Pract. 166, 118–134.

Wang, M.M., Jia, Z.Y., 2024. Investigating the correlation between building façade design elements and tourist satisfaction-Cases study of Italy and The Netherlands. Habitat Int. 144. https://doi.org/10.1016/j.habitatint.2024.103001.

Zhang, D.F., Shen, Z.F., Li, Y.L., 2023. Requirement analysis and service optimization of multiple category fresh products in online retailing using importance-Kano analysis. J. Retailing Consum. Serv. 72. https://doi.org/10.1016/j.jretconser.2022.103253.

Zhang, C.X., Xu, Z.S., 2024. Gaining insights for service improvement through unstructured text from online reviews. J. Retailing Consum. Serv. 80. https://doi.org/10.1016/j.jretconser.2024.103898.

Zhao, X.Q., Huang, Z., 2024. A method for exploring consumer satisfaction factors using online reviews: a study on anti-cold drugs. J. Retailing Consum. Serv. 81. https://doi.org/10.1016/j.jretconser.2024.103895.

Zheng, J., Lienert, J., 2018. Stakeholder interviews with two MAVT preference elicitation philosophies in a Swiss water infrastructure decision: aggregation using SWING-weighting and disaggregation using UTA GMS. Eur. J. Oper. Res. 267 (1), 273–287.

Zhu, B., Guo, D.F., Ren, L., 2022. Consumer preference analysis based on text comments and ratings: a multi-attribute decision-making perspective. Inf. Manag. 59 (3). https://doi.org/10.1016/j.im.2022.103626.

Zopounidis, C., Doumpos, M., 1999. A multicriteria decision aid methodology for sorting decision problems: the case of financial distress. Comput. Econ. 14 (3), 197–218.