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Learning consumer preferences from online textual reviews and ratings based on the aggregation-disaggregation paradigm with attitudinal Choquet integral

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ABSTRACT

Online reviews contain a wealth of information about customers' concerns and sentiments. Sentiment analysis can mine consumer preferences and satisfaction over products/services. Most existing studies on sentiment analysis only considered how to extract attribute types or attribute values of products/services from textual reviews, but ignored the role of attribute-level ratings in reflecting consumer preferences and satisfaction. Based on sentiment analysis and preference disaggregation, this paper unifies the quantitative and qualitative information extracted from attribute-level ratings and textual reviews, respectively, to obtain attribute types and attribute values of products/services. To acquire individual consumer preferences concerning product/service attributes, this paper proposes a method within an aggregation-disaggregation paradigm based on the attitudinal Choquet integral to transform overall online ratings into the form of pairwise comparisons. Compared with the additive value function used in most studies, more consumer preferences in terms of the importance of attributes, the interactions between pairwise attributes, and the tolerance of consumers to make compensation between attribute values in the aggregation process can be deduced by our proposed method. Several real cases on TripAdvisor.com are given to show the applicability of the proposed method.

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1. Introduction

Due to the continuous development of social media, online reviews (or user-generated content) have been viewed as a promising data source for firms to learn and monitor consumer preferences over their products (Li et al., 2020; Tan et al., 2018). Consumer preference analysis has been a central problem in marketing (Farias & Li, 2019). Capturing consumer preferences from online reviews is important in today's online environment (Li et al., 2020). The more valid information about consumer preferences

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that third-party platform owners and firm managers can extract from the huge volume of online reviews, the better operations, and marketing strategies (e.g., product recommendation, product pricing, market segmentation) they can design for greater profitability. In this regard, how to extract or learn consumer preferential information hidden in online reviews is an important research issue.

In the paradigm of multi-attribute utility theory (MAUT) (Keeney & Raiffa, 1976), value functions were considered as preference models for eliciting consumer preferences and providing insights on how a consumer evaluates a product or service and why he or she likes it (Guo et al., 2020). This study aims to aid consumer preference analysis from online reviews based on value functions. Generally, there are three steps to elicit preferences in the form of value functions: (1) product selection and product attribute extraction; (2) modeling a marginal value function to derive product attribute value; (3) developing a global value function to aggregate marginal attribute values of an alternative on different attributes.

The techniques of product attribute extraction have been well-established, and an overview can be viewed in Fan et al. (2020). However, when it comes to determining attribute types and values based on online reviews, there is a notable fact that the evaluation value of a product under an attribute may be placed in different types of online reviews, such as textual reviews, star ratings, or both of them. Textual reviews are detailed textual descriptions of consumer evaluation and satisfaction of a product over various aspects, while star ratings consist of both the overall rating on the comprehensive performance of a product and the attribute-level ratings on the performance of a product concerning different attributes. As reviewed by Fan et al. (2020), a large body of literature utilized textual reviews or attribute-level ratings separately, which might result in incomplete information extraction about the evaluation values of product attributes in terms of types and values (this issue will be explained in detail in Section 3.1). To solve this issue, in this paper, we shall purpose a method to acquire attribute types and values revealed by consumers by considering both attribute-level ratings and textual reviews, thus reducing the possibility of incomplete extraction of consumer evaluation information.

How to choose an appropriate global value function to approximate the preference structures of consumers is another challenge. Value functions can be linear functions or non-linear functions (Branke et al., 2016), reflecting the diverse preferences of consumers in aggregating attribute values. The essence of aggregation is to make trade-offs between the evaluation values of diverse attributes (Cinelli et al., 2020). Different consumers have different degrees of tolerance for compensating bad attribute values with good attribute values (Aggarwal, 2018). It is necessary to consider a value function leaving room for adjusting the attitude of compensation in the aggregation process. This is the second issue that we would like to solve in this study.

A complex value function requires consumers to provide a considerable amount of preference information, such as the values of model parameters (Branke et al., 2016; Doumpos & Zopounidis, 2011). This direct way is not enough applicable in reality because it increases the workload and time consumption of consumers. Multiple attribute decision making (MADM) approaches based on indirect preference information given by consumers and on the preference disaggregation paradigm (Doumpos & Zopounidis, 2011; Jacquet-Lagrèze & Siskos, 2001) are helpful to reduce the cognitive efforts of consumers. Ordinal regression (Jacquet- Lagrèze & Siskos, 1982) is a common preference disaggregation method, which aims to infer the parameters of preference structure from a set of reference alternatives provided by consumers. The classical ordinal regression method considered only a specific set parameter of a decision model. Since such a choice regarding the set of parameters is arbitrary, the robust ordinal regression (ROR) was proposed to consider all the sets of parameters compatible with a consumer's preference information (Greco et al., 2008). Then, the ROR was applied to MAUT (Jacquet-Lagrèze & Siskos, 1982, Siskos et al., 2016) for considering the whole set of additive value functions compatible with preference information provided by the consumer, which is collectively called the additive robust ordered regression. Considering that the additive robust ordered regression cannot represent preferences in the case of interactions between attributes, the non-additive robust ordered regression (NAROR) was constructed by introducing the idea of ROR into non-additive functions such as Choquet integral (Angilella et al., 2010, 2016; Corrente et al., 2016; Greco et al., 2014). The NAROR takes into account all the fuzzy measures which are compatible with the preference information for better describing the behaviors and preferences of a consumer. How to introduce the aggregation-disaggregation paradigm in NAROR for consumer preference analysis based on online comments is the third issue that we want to address in this paper.

In this study, an aggregation-disaggregation paradigm method based on the ACI is proposed to extract individual preference information from online reviews. Firstly, both attribute types and values are determined based on the information extracted from textual reviews and attribute-level ratings. Regarding textual reviews, the latent Dirichlet allocation (Blei et al., 2003) is used to extract the attribute types concerned by consumers, and the Recursive Neural Tensor Network method (Socher et al., 2013) is adopted to extract possible sentiment tendencies and their probability distribution concerning each attribute, which are further transformed into the form of probabilistic linguistic term sets (PLTSs) (Pang et al., 2016). Concerning attribute-level ratings, we construct a linear programming model to calculate attribute values close to individual consumer preferences. The attitudinal Choquet integral (ACI) (Aggarwal, 2018) takes into account three types of preferences, including the relative attribute importance, interactions among criteria, and the character of individual compensation attitude. The accuracy of ACI in predicting preferences has been proved experimentally by Aggarwal and Tehrani (2019). The ACI has also been successfully applied to establish a retrieval strategy in case-based reasoning (Fei & Feng, 2020). Thus, regarding the second issue concerning the compensation attitude of individuals, we adopt the ACI as a global value function to model the individual preferential structure from online reviews. In this sense, we introduce the methodology of NAROR into the ACI to reduce consumers' cognitive pressure and further obtain more accurate consumer preferences. Furthermore, the aggregation-disaggregation paradigm in NAROR is introduced into the ACI model to obtain specific parameters reflecting the preferences of consumers. Several real cases about hotel evaluation on TripAdvisor.com[1] are given to show the applicability of the proposed method.

The contributions of this paper can be highlighted as follows:

1. A procedure on how to combine qualitative textual reviews and quantitative attribute-level ratings to extract attribute types and attribute values is proposed in this paper.
2. The ACI is employed as a preference model to approximate the preference structures of consumers, which can provide firm managers with more ideas about consumer preferences (e.g., the relative attribute importance, interactions among attributes, and the individual attitudinal character on compensation).
3. The combination of the ACI model and the aggregation-disaggregation paradigm in NAROR is established for eliciting consumer preferences hidden in online reviews without the participation of consumers. Both the ACI and the aggregation-disaggregation paradigm in the NAROR have not been used in consumer preference analysis based on online reviews.

The rest of this study is organized as follows: Section 2 reviews techniques for information extraction and representation from online reviews and the concept of the ACI. Section 3 proposes the procedure of extracting attribute types and values from both textual reviews and attributes-level ratings, and presents the detailed procedure of preference elicitation from online reviews based on the ACI within the aggregation-disaggregation paradigm. In Section 4, an illustrative case is given to show the proposed approach. Section 5 concludes the paper and presents future research directions.

2. Related work

This section mainly reviews the relevant processing methods of online reviews and the unification methods of quantitative and qualitative information. In addition, the theories of the ACI are also briefly summarized.

2.1. Short review on techniques for information extraction and representation from online reviews

Due to the unstructured characteristics of textual reviews, sentiment analysis (Pang et al., 2002) has been widely used to extract the hidden information about consumers' sentiment tendencies (e.g., positive, neutral, and negative) and intensities (e.g., strong and weak), which reflect consumers' satisfactions with products under different attributes. A summary of the use and classification of sentiment analysis techniques can be found in Fan et al. (2020). Considering that a textual review may contain many words or phrases with different sentiment intensities and orientations, using only an average sentiment score to describe the performance of a product is easy to cause evaluation information loss (Kang & Park, 2014). Compared with outputting an average sentiment score, extracting the sentiment tendencies and intensities of each attribute mentioned in the textual reviews can better reflect the reviewer's preference.

Among many sentiment analysis technologies, the Recursive Neural Tensor Network (RNTN) model (Manning et al., 2014; Socher et al., 2013) embedded in the Stanford Core NLP software package has high prediction accuracy in extracting consumers' sentiment tendencies and intensities for each attribute (Song & Chambers, 2014). The RNTN model, a deep learning model, can consider the influence of textual context and predict fine-grained sentiment of words into different degrees of positive/negative sentiment tendencies and their probabilities. These probabilities indicate the closeness of emotional words in textual reviews to corresponding sentiment tendencies. Through the use of the RNTN model, consumers' sentiment on each attribute embedded in textual reviews can be classified into different sentiment tendencies, such as 'very negative', 'negative', 'neutral', 'positive', and 'very positive', with corresponding probabilities, which can be transformed to PLTSs (Pang et al., 2016). In a PLTS, linguistic terms denote different sentiment tendencies and the probabilities of linguistic terms represent the corresponding probabilities and intensities of sentiment tendencies. For example, the above-mentioned five sentiment tendencies can be represented by a subscript-symmetric linguistic term set$s = \{s_{-2}, s_{-1}, s_0, s_1, s_2\}$. The sentiment tendencies and sentiment intensities of attribute 'food' in a textual review '*Good quality food, lagging service and strategically located on Las Vegas strip*' can be extracted by the RNTN model in the Stanford Core NLP soft package as {'very negative' (0), 'negative' (0), 'neutral' (0.09), 'positive' (0.59), 'very positive' (0.32)}. This result of sentiment analysis can be transformed into a PLTS$\{s_{-2}(0), s_{-1}(0), s_0(0.09), s_1(0.59), s_2(0.32)\}$. The probabilities of five linguistic terms mean the closeness of the emotional words 'good' used to describe attribute 'food' in the review to the five linguistic terms in terms of sentiment intensity and tendency.

The PLTS is an efficient tool to represent sentiment tendencies and intensities hidden in unstructured text reviews. Several studies have applied PLTSs to represent linguistic evaluations in textual reviews for multi-attribute online product ranking problems under uncertainty. For example, Peng et al. (2018) introduced probabilistic linguistic information to select hotels based on a cloud decision support model. Based on the Blair-Goldensohn model, Liu and Teng (2019) used PLTSs to represent the sentiment analysis results of textual reviews given by each reviewer. Liang et al. (2020) utilized PLTSs and the long short-term memory together to describe consumers' sentiments on the attributes of web celebrity shops. Due to the flexibility of the RNTN model, some studies acquired the sentiment analysis results of textual reviews easily and expressed the results by PLTSs (Wu & Liao, 2021a, 2021b; Zhang et al., 2021; Zhao et al., 2022). Inspired by this, this paper comes with PLTSs with five sentiment levels to represent the sentiment analysis results of textual reviews extracted by the RNTN model.

2.2. The unification of quantitative and qualitative information in online reviews

The separate use of attribute-level ratings or textual reviews is inadequate to accurately extract the preferences of consumers. Textual comments provide evaluations of product attributes in detail, whereas what specific meaning consumers want to express cannot be represented with a single numeric measure such as ratings (Fang et al., 2016, Godnov & Redek, 2019). But, a star rating directly shows the global measurement of a customer's perception and satisfaction with a product. In this sense, it is necessary to propose a unified method to harness the information of both ratings and textual reviews over different product attributes.

Generally, there are two methods to unify quantitative ratings and qualitative textual reviews (Santos et al., 2017). One method is to first convert qualitative comments to quantitative data, and then regularize both the transformed qualitative comments and quantitative ratings into values between 0 and 1 (Ahani et al., 2019; Jin et al., 2019; Zhang et al., 2021). The other is to translate quantitative data into linguistic representations. Since unstructured textual reviews with random characteristics cannot be analyzed directly for decision analysis, it is necessary to convert qualitative information included in textual reviews into quantitative information. Thus, in this paper, we utilize the first method to unify quantitative and qualitative information.

2.3. The attitudinal Choquet integral

Most of the conventional value functions (e.g., the additive value function) are compensative value functions in which the bad performance of an alternative under several attributes can be compensated by the good performance of the alternative under other attributes (Aggarwal, 2018). These compensative value functions only can cope with the situation where the evaluation attributes are all independent of each other. However, the restrictive hypotheses of the preferential independence among attributes (Keeney & Raiffa, 1976) cannot be met all the time due to the interactions among attributes (Aggarwal & Tehrani, 2019; Greco et al., 2014).

The Choquet integral (Choquet, 1954), a representative non-additive value function, considers the interdependence among different attributes and utilizes the fuzzy measure $\mu(\cdot)$ to capture the importance degrees of attributes and subsets of attributes. The attitudinal Choquet integral (ACI), an extension of the Choquet integral, is capable of considering the interactions between attributes and the attitudinal character of a DM towards the degrees of andness[2] or orness[3] in the aggregation process. Thus, the ACI operator is more apt to depict the individualistic aggregation behavior of a consumer due to its ability in representing the importance of attributes, interactions among criteria, and an individual's attitudinal tendencies for aggregation, simultaneously.

An ACI of dimension n is a mapping $ACI : [0,\ 1]^n \rightarrow [0,\ 1]$, given as

$$ACI_{\mu,\lambda}(f(c_1),...,f(c_n)) = \log_\lambda \left(\sum_{j=1}^{n} \left[\mu(A_j) - \mu(A_{j+1})\right] \lambda^{f(c_{\delta(j)})} \right) \tag{1}$$

where $\lambda \in (0, \infty], \lambda \neq 1$. $f(c_j)$ is the attribute value of an alternative under attribute c_j $(j = 1,...,n)$. $\delta(\cdot)$ is the permutation of $\{1,...,n\}$ such that $0 \leq f(c_{\delta(1)}) \leq ... \leq f(c_{\delta(n)})$, and $A_j = \{c_{\delta(j)}, c_{\delta(j+1)}, .., c_{\delta(n)}\}$ is a subset of $n-j+1$ components in the attribute set $C = \{c_1,...,c_n\}$ with $A_{(n+1)} = \emptyset$. $\mu(\cdot)$ indicates the weight or the capacity of an attribute subset. The set function $\mu : 2^C \rightarrow [0,1]$ needs to satisfy: $\mu(\emptyset) = 0, \mu(C) = 1,$ and $\mu(A) \geq \mu(B), \forall B \subseteq A \subseteq C$. The parameter λ reflects the degree of compensation in the aggregation process. If a DM accepts that the good performance under one attribute compensates for the poor performance under other attributes, a high value of λ can be given. When $\lambda \rightarrow 0$ (or $\lambda \rightarrow \infty$), the minimum (or the maximum) of the aggregation results can be obtained. When $\lambda \to 1$, the ACI reduces to the conventional Choquet integral.

To ease the computation of the ACI, the Möbius representation of the capacity μ was introduced to the ACI (Aggarwal, 2018; Chateauneuf & Jaffray, 1989), such that

$$ACI_{\mu,\lambda}(f(c_1),\ldots,f(c_n)) = \log_\lambda\left(\sum_{T\subseteq C} m^\mu(T)\lambda^{\min\{f(c_j)|j\in T\}}\right) \tag{2}$$

where $m^\mu(\emptyset)=0$, $\sum_{T\subseteq C} m^\mu(T)=1$, $m^\mu(\{c_j\})\geq 0, \forall c_j\in C$ and $\forall S\subseteq C\backslash\{c_j\}$, $m^\mu(\{c_j\})+\sum_{T\subseteq S} m^\mu(T\cup\{c_j\})\geq 0$, for all$j=1,\ldots,n$. When $f(c_1)=f(c_2)=,\ldots,=f(c_n)=\eta$, $\eta\in[0,1]$, there is $ACI_{\mu,\lambda}(f(c_1),\ldots,f(c_n))=\eta$[4].

Note that it is not easy to assign weights for all possible attribute subsets with interactions. In real cases, allowing consumers to consider the interactions between multiple attributes will increase the complexity of the evaluation process. To simplify this matter, we take into account only interactions between a couple of attributes. Specifically, in terms of the Möbius representation, each attribute c_j has a value $m^\mu(\{c_j\})$ and each pair of attributes $\{c_j,c_k\}$ has a value $m^\mu(\{c_j,c_k\})$. The weight that a 2-additive capacity μ (Grabisch, 1997) assigns to a set $T\subseteq C$ can be expressed in terms of the Möbius representation as follows:

$$\mu(T)=\sum_{j\in T} m^\mu(\{j\})+\sum_{\{j,k\}\subseteq T} m^\mu(\{j,k\}),\ \forall T\subseteq C,\ j\neq k \tag{3}$$

where $m^\mu(\{j\})=m^\mu(\{c_j\})$, $m^\mu(\{j,k\})=m^\mu(\{c_j,c_k\})$ for short. The boundary and monotonicity of the capacity can be transformed into the following forms, respectively:

$$m^\mu(\emptyset)=0,\ \sum_{j\in C} m^\mu(\{j\})+\sum_{\{j,k\}\subseteq C} m^\mu(\{j,k\})=1 \tag{4}$$

$$m^\mu(\{j\})\geq 0,\quad \forall j\in C \tag{5}$$

$$m^\mu(\{j\})+\sum_{k\in T} m^\mu(\{j,k\})\geq 0,\quad \textit{for all } j\in C,\ \textit{and for all } T\subseteq C\backslash\{j\},\ T\neq\emptyset \tag{6}$$

In this case, Eq. (2) can be converted to

$$ACI_{\mu,\lambda}(f(c_1),\ldots,f(c_n)) = \log_\lambda(\sum_{j\in C} m^\mu(\{j\})f(c_j)+\sum_{\{j,k\}\subseteq C} m^\mu(\{j,k\})\lambda^{\min\{f(c_j),f(c_k)\}}) \tag{7}$$

3. A method to learning consumer preferences from online textual reviews and ratings

This section first explains the research problem we would like to solve in this study, and then describes the process of extracting attribute types and determining attribute values based on textual reviews and attribute-level ratings. The method of learning consumer preferences from online reviews based on the ACI within an aggregation-disaggregation paradigm is also given in this section.

3.1. Problem description

A set of attributes can be found or collected in a consumer's online reviews, which include attribute-level ratings and textual reviews about a class of products. Consumers may leverage different attributes to evaluate products within the same category, or post reviews of products with respect to several attributes in different places. As shown in Figure 1, the traveler 'Tanja' utilized six attributes to evaluate a hotel and post his/her reviews including the overall ratings, textual reviews, and attribute-level ratings. Specifically, the evaluations of attribute 'service' appeared in both textual reviews and ratings on multi-attribute, but the evaluations of other attributes (like 'food', and 'sleep') are either in textual reviews or in ratings on multi-attribute. The goal of this study is to integrate the information hidden in textual comments and attribute-level ratings provided by individual consumers to obtain the attribute types and attribute values for each product. The information obtained about product attributes is then utilized to analyze individual consumers' preferences and understand their decision-making behaviors. It is worthy to highlight that in MADM, the value function and marginal value function are not elicited directly according to the preference data haven from DMs, but usually are predefined as a subjective approximation of actual preferences of DMs. In this study, we just simply assume that there is a particular shape of the value function which obtains the overall evaluation value of an alternative by aggregating the performance of the alternative under the given attributes.

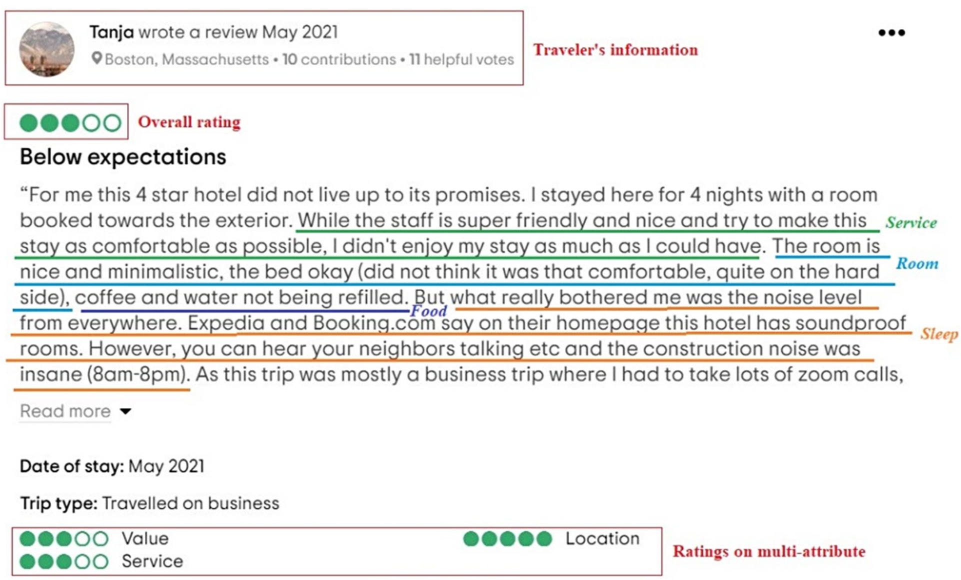

Figure 1. An illustration of online reviews on TripAdvisor.com.
Source: cited from Tripadvisor.com and edited by authors.

Table 1. Some notations used in the paper.

Notation	Description
$A = \{a_1, a_2, \ldots, a_m\}$	A set of products/services in the same category, where a_i denotes the ith product/service
$C = \{c_1, c_2, \ldots, c_n\}$	A finite set of product/service attributes, where c_j denotes the jth attribute
$R = \{R_1, R_2, \ldots, R_m\}$	A set of the overall rating of m products/services
$T = \{T_1, T_2, \ldots, T_m\}$	Textual review associated with m products/services, where T_i denotes textual comments for the ith product/service
$t_i = \{t_i^1, t_i^2, \ldots, t_i^n\}$	Results of sentiment analysis of textual comment T_i denoted in PLTSs. t_i^j means a PLTS under the jth attribute for the th product/service
	Attribute-level ratings for the ith alternative under n attributes
$U(a_i)$	The overall value of product/service a_i
$u(t_i^j)$	The sentiment score of the PLTS t_i^j
$u(r_i^j)$	The marginal attribute value of the attribute-level rating r_i^j
$u(a_i^j)$	The marginal attribute value of product/service a_i under attribute c_j.

Source: created by the authors.

The objective of this study can be disaggregated into the following issues: (1) how to transform the qualitative information in textual reviews into quantitative information (see Sect. 3.2.1); (2) how to determine attribute values hidden in attribute-level ratings (see Sect. 3.2.2); (3) how to integrate the quantitative information transformed from textual reviews and attribute-level ratings to obtain attribute types and values of different products evaluated by the same consumer (see Sect. 3.2.3); (4) how to introduce the ACI to the aggregation-disaggregation paradigm for approximately expressing the preference structure of a consumer (see Sect. 3.3). We will solve these issues one by one in the next section. To simplify presentation and facilitate understanding, the notations used in this study are listed in Table 1.

3.2. Extracting consumer preferences from online textual reviews and ratings

Considering that online reviews cannot be directly used for analysis, the processes of mining useful information, including the attribute types concerned by consumers and the performances of products/services under each attribute, from online reviews need to be conducted. The ways of mining information from different types of online reviews are different. This section introduces methods of mining and integrating information from online reviews.

3.2.1. The extraction and transformation of qualitative information in textual reviews

Mining attribute types and attribute values from textual reviews requires the methods of attribute extraction and sentiment analysis (Fan et al., 2020). Several studies have shown the effectiveness and reliability of Latent Dirichlet allocation (LDA) (Blei et al., 2003) in extracting attribute types of products/services from online reviews (Bi et al., 2019; Guo et al., 2017; Zhang et al., 2021). In this study, the LDA, which is an unsupervised machine learning technique, is used to extract the frequently expressed topics (attributes) and topic-related keywords from textual reviews.

Prior to extracting attribute types and values, the collected textual reviews should be examined and preprocessed using the following sequential steps (Zhang et al., 2021): 1) Filter out some kinds of textual reviews, such as duplicate reviews, non-

English characters and words, uninformative reviews[5], less than five words, and inconsistent reviews[6]. 2) For each textual review of a product/service, eliminate punctuations and stop words (e.g., a, an, the), substitute all capital letters with lower-case letters, and transform all English letters into the same format. 3) Divide each textual review into different words through the technique of word segmentation, tag the correct part-of-speech for segmented words, change the different forms of word roots into the original forms by the stemming algorithm and lemmatization, and remove the words that appear frequently but are not related to the product/service by the list of stop words.

For a given set of textual reviews, various words with a certain meaning can be obtained by the generative process of LDA. A group of words with the same or similar meanings can form a set which can be summarized into a topic. Considering that there may be some noisy words irrelevant to existing topics, it is allowed to filter these noisy words in each topic and only retain the topic-related keywords. Each textual review can be viewed as a mixture of multiple topics, and each topic includes a set of topic-related keywords extracted from textual comments. If similar topics exist, they should be manually merged into one topic. In this paper, we manually merge similar topics in line with the rule conducted by Zhang et al. (2021). The final retained topics can be regarded as attribute types of a product/service.

To determine the product/service attribute values from textual reviews, sentiment analysis needs to be used to mine the sentiment information reflecting comprehensive opinions of consumers on product/service attribute types. Based on the extracted product attributes and corresponding keywords, in this study, the RNTN model is utilized to analyze related sentiment tendencies and intensities of each attribute in textual reviews. The specific processes of attribute extraction based on the LDA model and the sentiment analysis based on the RNTN model mainly refer to the work of Zhang et al. (2021). PLTSs are used to represent consumers' sentiment tendencies and intensities on product attributes according to the sentiment analysis results deduced from the RNTN model.

A subscript-symmetric linguistic term set $S = \{s_{-2}, s_{-1}, s_0, s_1, s_2\}$ represents the possible five sentiment tendencies from 'strongly negative' to 'strongly positive'. The sentiment intensity of s_α indicates the frequency of this sentiment tendency used to describe product attributes. For a textual review T_i of product a_i, the value of a_i on attribute can be represented as:

$$t_i^j = \begin{cases} \emptyset, & \text{if the } j\text{th attribute is not reviewed in } T_i \\ \{s_\alpha(p_\alpha) | \alpha = -2, \ldots, 0, \ldots, 2\}, & \text{otherwise} \end{cases} \tag{8}$$

where t_i^j is a PLTS including a set of linguistic terms and their possible probabilities when the attribute c_j is reviewed in T_i. There is $\sum_{\alpha=-2}^{2} p_\alpha = 1$, which means that the complete information of the probabilistic distribution of all possible linguistic terms is derived.

The sentiment analysis results of textual reviews reflect the consumer's perceptions of the product/service regarding related attributes, and can be regarded as the actual performances of the product/service under the related attributes. In this sense, sentiment scores inferred from sentiment analysis can be used as attribute values, reflecting the performance of the product/service on attributes.

Based on the expectation function of PLTSs (Wu et al., 2018), the sentiment score of t_i^j can be estimated as

$$u(t_i^j) = \sum_{\alpha=-2}^{2} \left(\frac{\alpha + 2}{4} p_\alpha \right) / \sum_{\alpha=-2}^{2} p_\alpha \tag{9}$$

where $0 \leq u(t_i^j) \leq 1$. Especially, $u(t_i^j) = 1$ if and only if $t_i^j = \{s_2(p_2)\}$, and $u(t_i^j) = 0$, if and only if $t_i^j = \{s_{-2}(p_{-2})\}$. In this way, the qualitative information in textual review can be converted into quantitative information with the value between 0 and 1, which can be unified with the quantitative information extracted from attribute-level ratings.

3.2.2. Attribute types and values associated with attribute-level ratings

Product attribute types corresponding to attribute-level ratings can be obtained directly by the techniques of online review crawling. But for attribute values, we need to convert the attribute-level ratings into utility values in the range of [0, 1], instead of using them directly. To this end, marginal utility functions need to be introduced to drive attribute values of the ratings on multiple attributes. Many studies have discussed the specific form of marginal value functions regarding different attributes. Rezeai (2018) and Wu and Liao (2021b) have discussed specific forms of marginal value functions such as a spectrum of piecewise value functions and the exponential value function, to evaluate alternatives with respect to different attributes.

Due to different features of evaluation attributes and personalized cognition of consumers, the simple linear value function is inappropriate to measure attribute values of a product under all given attributes. When calculating attribute values of a product under different attributes, it is not necessary to consider the diverse unit dimensions[7] of attributes. The higher the rating on an attribute is, the greater the attribute value of a product under this attribute. Considering that a small difference in an attribute value between adjacent ratings at both ends may exist and different consumers may have different evaluation benchmarks (Wu & Liao, 2021b), we employ a non-linear but monotonically increasing marginal value function to approximate attribute values of a product on multiple attributes corresponding to a consumer. It is worthy to highlight that the actual marginal value function of a product under an attribute is usually unknown. We can only predefine the form of the marginal value function to approximately express the decision behavior of a consumer.

The mixed exponential function (MEF) (Wu & Liao, 2021b) with a smooth shape can flexibly measure the concavity and convexity of attribute value changes. We choose the monotonically increasing MEF to calculate the values of attribute-level ratings. Considering that the attribute-level ratings have five levels, the 3-rating is taken as the benchmark of the cognition curve. Then, the value of the attribute-level rating r_i^j can be calculated as

$$u_{MEF}(r_i^j) = \begin{cases} \dfrac{(\beta_1 + N(r_i^j))^{\gamma_1}}{(\beta_1 + N(r_i^j))^{\gamma_1} + (\beta_1 - N(r_i^j))^{\gamma_1}}, & if\ r_i^j \le 3 \\ \dfrac{(\beta_2 + N(r_i^j))^{\gamma_2}}{(\beta_2 + N(r_i^j))^{\gamma_2} + (\beta_2 - N(r_i^j))^{\gamma_2}}, & if\ r_i^j > 3 \end{cases} \tag{10}$$

$$N(r_i^j) = \frac{r_i^j - 3}{2} \tag{11}$$

where $N(r_i^j)$ is the normalized value of r_i^j, $r_i^j \in \{1, 2, ..., 5\}, N(r_i^j) \in [-1, 1]$. When $N(r_i^j) \in [-1, 0]$, $u(r_i^j) \in [0, 0.5]$ and if $N(r_i^j) \in [0, 1]$, then $u(r_i^j) \in [0.5, 1]$. The parameters γ_1 and γ_2 are used to control the convexity and concavity of the marginal utility function. If $\gamma_1, \gamma_2 \in (0, 1)$, the shape of the marginal value function is concave; if $\gamma_1, \gamma_2 > 1$, the shape is convex; if $\gamma_1, \gamma_2 = 1$, the shape is linear. Given that a 5-star rating does not always mean the most satisfactory product performance, two parameters β_1 and β_2 are set to limit the attribute values of a product's ratings under different attributes. We set $\beta_1, \beta_2 \ge 1$. In this way, the attribute value of a 1-star rating can be larger than 0 and the attribute value of a 5-star rating cannot be greater than 1. In addition, if $N(r_i^j) \to -\beta_1$, then $u(r_i^j) \to 0$, while if $N(r_i^j) \to \beta_2$, then. When $\beta_1 = \beta_2, \gamma_1 = \gamma_2$, the shape of the marginal value function is smooth; otherwise, the shape has segment points. The values of all unknown parameters $(\gamma_1, \gamma_2, \beta_1, \beta_2)$ need to be determined from historical online reviews published by consumers, rather than directly given by consumers. Preference disaggregation (Doumpos & Zopounidis, 2011; Jacquet-Lagrèze & Siskos, 2001) helps indirectly infer the parameters of marginal value functions from a set of decision examples through a linear programming model, so as to reduce the burden on consumers in decision making.

As shown in Figure 1, online reviews about a product under an attribute may be posted in both textual reviews and attribute-level ratings. For a consumer, the evaluation of an attribute of a product should be stable, that is, the attribute value extracted from textual reviews should be equivalent to that deduced in attribute-level ratings. Based on this assumption, Model 1 is constructed to derive the values of parameters in a pre-defined marginal value function given as Eq. (10).

Model 1

$$\min\ \mathrm{F}_2 = \sum_{k=1}^{K} (\delta_k^+ + \delta_k^-)$$

$$s.t.: \begin{cases} u(t_i^j)_k - u_{MEF}(r_i^j)_k + \delta_k^- - \delta_k^+ = 0 \\ \gamma_1, \gamma_2 > 0 \\ \beta_1, \beta_2 > 1 \\ \delta_k{}^-, \delta_k{}^+ \ge 0 \end{cases} \tag{12}$$

where δ_k^+, δ_k^- are error variables to adjust the differences between the values of textual reviews and attribute-level ratings. The values of products under a certain attribute can be used as input information for Model 1 only if both textual reviews and the ratings for that attribute are presented, so K denotes the number of times that textual reviews and attribute-level ratings describing a certain attribute are presented simultaneously in the collected online reviews. In short, Model 1 has $K+6$ constraints.

The goal of Model 1 is to minimize the errors of attribute values. The value of $u(t_i^j)$ is obtained by Eq. (9), and the specific values of unknown parameters can be learned by Model 1. Then, the marginal value function with learned parameters can be used to calculate the values of other attributes only evaluated by ratings on attributes. For Model 1, since not all attributes are mentioned in textual reviews and attribute-level ratings at the same time, the size of $K$is limited, and thus the number of constraints is small. Hence, Model 1 is a linear programming model, which can be solved using the optimization package in Lingo or MATLAB and does not take much time.

3.2.3. Determination of attribute values

In order to integrate qualitative and quantitative information, we propose four rules to determine the value of alternative a_i under attributec_j :

1. When the evaluation of a product on an attribute is only presented in textual reviews, the attribute value is the sentiment score of the product on this attribute in textual reviews derived by Eq. (9).

$$u(a_i^j) = u(t_i^j) \tag{13}$$

where $u(t_i^j)$ is the attribute value of alternative a_i under attribute c_j extracted from textual reviews.

1. When the evaluations of a product on an attribute is only posted in attribute-level ratings, the attribute value is equal to the value derived Eq. (10). That is,

$$u(a_i^j) = u(r_i^j) \tag{14}$$

where $u(r_i^j)$ is the attribute value of alternative a_i under attribute c_j.

1. If the evaluations of an attribute are simultaneously posted in textual reviews and attribute-level ratings, the attribute value is given by the weighted average of the sentiment score of textual reviews and the value of attribute-level rating. That is,

$$u(a_i^j) = \frac{1}{2}u(t_i^j) + \frac{1}{2}u(r_i^j) \tag{15}$$

2. If there is an attribute that is mentioned in neither textual reviews nor attribute-level ratings, the attribute value of this attribute is unknown. The product/service attributes may not be evaluated because of some evaluation behavior. For example, consumers are not willing to evaluate or are not interested in some attributes of the product. Consumers may only be willing to disclose the evaluations of attributes which are more important to them or the evaluation values of

attributes are extreme (either 'very good' or 'very poor') in online reviews. Generally speaking, if a consumer is concerned about specific attributes of a product, the consumer will actively express his/her true opinion in online reviews, no matter whether the attribute evaluation is positive or negative. In the context of MADM, using marginal value function to extract consumer preferences needs to meet the premise that the evaluated product must have evaluation values under all preset attributes. In order to deal with the problem that some attributes have not been evaluated in online reviews, we assume that the attributes that have not been evaluated are less important to consumers than the mentioned attributes, and the attribute values of those attributes that have not been evaluated are intermediate values, taking 0.5 in the range of [0, 1].

Through the mentioned methods above, the qualitative and quantitative information hidden in online reviews can be derived and combined for further analysis of consumer preferences.

3.3. Learning consumer preferences based on the ACI within the aggregation-disaggregation paradigm

Usually, it is difficult for consumers to provide values of all parameters of the considered preference model. Instead of providing the values of parameters in a preference model subjectively, the aggregation-disaggregation paradigm can infer parameter values of the chose preference model indirectly relying on a small amount of preference information provided by consumers.

The preference information provided by consumers includes but not limited to the forms of pairwise preference comparisons on alternatives, and pairwise comparisons of the importance of attributes. It is worth noting that, in this paper, we conduct consumer preference analysis based on online comments released by consumers. In other words, the preference information needs to be obtained from online comments rather than provided by consumers. From online reviews, we can infer pairwise preference comparisons on products/services according to the comparisons of the overall ratings which reflect the overall satisfaction of consumers with products/services. The higher the overall ratings are, the better the performance of products/services are. Thus, this paper takes the pairwise preference comparisons of products/services deduced from the comparisons of overall ratings as the preference information supplied by consumers. We should note that it is difficult to get the preference information about attribute importance directly from online comments.

There are three commonly used types of preference relations of alternatives, which are preferential, indifferent and weak preference order, respectively (Keeney & Raiffa, 1976). The preferential preference relation $a_1 \succ a_2$ means that alternative a_1 is strictly superior to a_2. The indifferent relation $a_1 \sim a_2$ denotes that is as good as a_2. The weak preference relation described as $a_1 \succeq a_2$ means that a_1 is at least as good as a_2, which can be seen as a combination of preferential and indifferent relations. For consumers, there is a small difference of products with adjacent ratings on an attribute. For example, products with an overall rating of five are not always better than products with an overall rating of four, but products with an overall rating of five have more advantages than products with an overall rating of no more than three. Thus, in this study, we only consider the preferential preference relation between products/services with obvious difference in overall ratings to reduce inference errors.

Suppose that two products $(a_1,)$ are evaluated under two attributes (c_1, c_2) and their marginal values under attributes are $f_i(c_j), i \in \{1,2\}, j \in \{1,2\}$. There is a preferential relation $a_1 \succ a_2$. The attitudinal Choquet integral (ACI) is used to aggregate the performance values of two products under two attributes as follows:

$$\begin{aligned} ACI_{\mu,\lambda}(a_1) > ACI_{\mu,\lambda}(a_2) \iff & \log_\lambda(m^\mu(\{c_1\})\lambda^{f_1(c_1)} \\ & + m^\mu(\{c_2\})\lambda^{f_1(c_2)} + m^\mu(\{c_1,c_2\})\lambda^{\min\{f_1(c_1),f_1(c_2)\}}) \\ > \log_\lambda(m^\mu(\{c_1\})\lambda^{f_2(c_1)} & + m^\mu(\{c_2\})\lambda^{f_2(c_2)} + m^\mu(\{c_1,c_2\})\lambda^{\min\{f_2(c_1),f_2(c_2)\}}) \end{aligned} \tag{16}$$

Based on the preference information collected from the overall ratings of products, an aggregation-disaggregation paradigm is introduced to elicit compatible fuzzy measures and the consumer's characters towards the compensation degree in the aggregation process. The part of aggregation means the process of aggregating the performance values of products under all attributes based on the ACI, while the part of disaggregation refers to constructing nonlinear constraints shown in Model 2 for utilizing individual consumer's preference information.

Model 2

$$\max \ \varepsilon$$
$$s.t. \begin{cases} ACI_{\mu,\lambda}(a) > ACI_{\mu,\lambda}(b) + \varepsilon & \text{with } a \succ b, \ \text{a, b} \in A' \\ \lambda > 0, \lambda \neq 1 & \\ m^\mu(\emptyset) = 0 & \\ \sum_{j \in C} m^\mu(\{j\}) + \sum_{\{j,k\} \subseteq C} m^\mu(\{j,k\}) = 1, & \forall j,k \in C \\ m^\mu(\{j\}) \geq 0, & \forall\ j \in C \\ m^\mu(\{j\}) + \sum_{k \in T} m^\mu(\{j,k\}) \geq 0, & \forall j \in C, \text{ and } \forall \mathrm{T} \subseteq \mathrm{C} \backslash \{j\}, \ T \neq \emptyset \\ u(\{j\}) < u(\{j,k\}), & \forall j,k \in C \\ u(\{k\}) < u(\{j,k\}), & \forall j,k \in C \\ u(T) < 1, & \forall T \subset C \\ v^\mu(\{j\}) = u(\{j\}) + \frac{1}{2} \sum_{k \in C \backslash j} m^\mu(\{j,k\}), & \forall j,k \in C \\ \sum_{j \in C} v^\mu(\{j\}) = 1 & \end{cases} \tag{17}$$

The goal of Model 2 is to maximize the difference between the products with a preferential relation. The parameter ε is a constraint coefficient to ensure that the strict inequalities are established. $\varepsilon^* = \max\varepsilon$ is the maximal value of ε obtained from the solution of Model 2. The monotonicity and boundary conditions of fuzzy measures need to be hold. According to Eq. (3), when there is an interaction between attributes c_j and c_k, then, $u(\{j,k\}) = u(\{j\}) + u(\{k\}) + m^{\mu}(\{j,k\})$, $u(\{j\}) = m^{\mu}(\{j\})$ and $u(\{k\}) = m^{\mu}(\{k\})$. At this time, $\mu(\cdot)$means the importance of an attribute subset allocated by the 2-additive capacity rather than the importance of a single attribute. The Shapley value of the 2-addtive capacity $\nu^{\mu}(\{j\})$ can be used to represent the importance of a single attribute (Grabisch, 1997).

From the perspective of MADM, consumers' intrinsic attribute preference is a constant. However, due to the different periods when consumers generate comments, their purchase psychology and preferences for different products are different, which will lead to the inconsistency between the preferences to attribute values and tolerances for product attributes with poor performance reflected in each comment. Thus, based on the historical comments generated by consumers over time, a certain set of parameters reflecting consumer preferences will be given to all products involved in the solution of Model 2. The pairwise comparisons of the aggregated values of products by the ACI are successively input in pairs to solve Model 2. If the constraints in Model 2 is feasible and $\varepsilon^{*}>0$, then there exists one set of fuzzy measures compatible with individual consumer's preference and the corresponding individual attitudinal character towards compensation in the aggregation process; if $\varepsilon^{*} \leq 0$, no feasible value function compatible with the preference information is found. We retain the preference information of pairwise comparison that makes $\varepsilon^{*}>0$, remove the preference information that makes Model 2 infeasible, and add new pairwise comparison information until the feasibility is restored. With enough pairwise comparison information about the overall ratings of individual consumers on products, at least one set of preference parameters can be obtained from Model 2 to reflect individual consumer's preferences without his/her participation.

3.4. The procedure of learning preferences of consumers from online textual reviews and ratings

In this section, the procedure to elicit the preferences of consumers through the ACI under the aggregation-disaggregation paradigm is established. For better understanding, the flowchart of the procedure of consumer preference analysis is shown in Figure 2.

Step 1: Collect all online reviews of an individual consumer on products in the same category, including overall ratings, ratings on different attributes, and textual reviews. Then, preprocess the collected online reviews according to the procedure described in Section 3.2.1.

Step 2: The LDA technique is used to mine attribute types from the retained textual reviews. Based on the determined attributes, the RNTN model is used to acquire sentiment tendencies and intensities over each attribute. The sentiment results are transformed into PLTSs for each attribute. The sentiment scores calculated by Eq. (9) are seen as the attribute values of products under each attribute in terms of textual reviews.

Step 3: Based on Model 1, unknown parameters in the marginal value function can be derived. The marginal value function is used to calculate the attribute values of other attribute-level ratings.

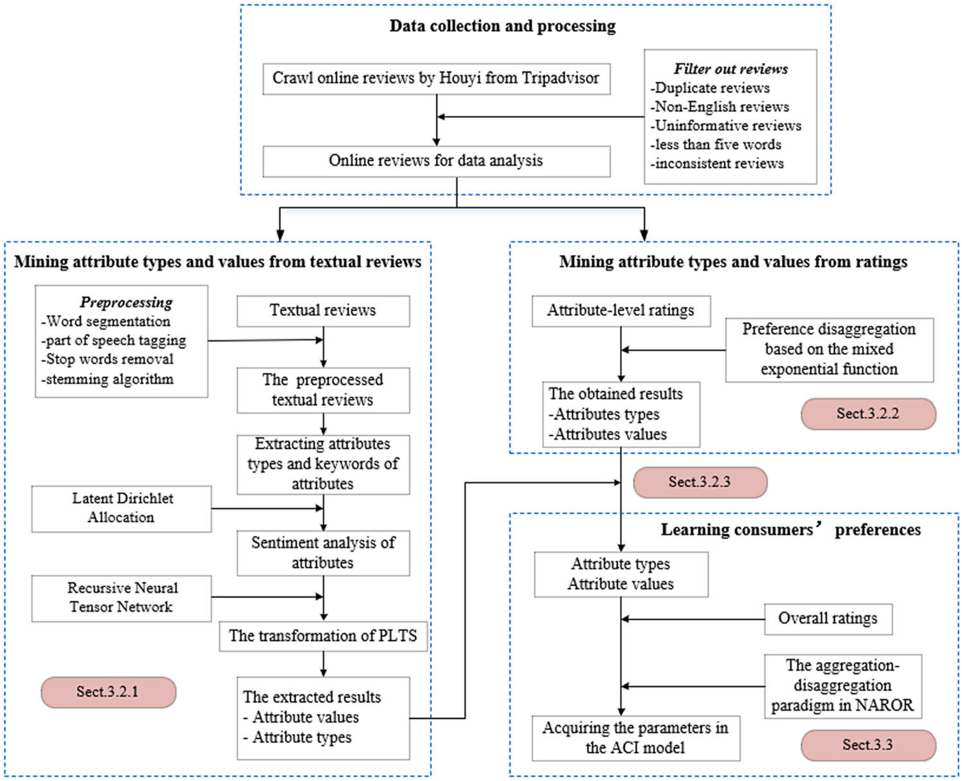

Figure 2. The flowchart of the procedure of consumer preference analysis.
Source: created by the authors.

Step 4: According to the rules in Section 3.2.3, we can get the marginal attribute values of all attributes closer to the preferences of the consumer.

Step 5: The comparison of overall ratings of any two products is taken as a preference pairwise comparison, which is used as the input information of Model 2. By solving Model 2, preference parameters of individual consumers including the importance of attributes, interactions between attributes, and the tolerance degree of the consumer to compensation between attribute values in the aggregation process can be deduced.

4. A numerical example

This section presents a real case on TripAdvisor.com to show the feasibility of the proposed method in learning individual consumer preferences.

4.1. Data collection

The used online reviews data are collected from Tripadvisor (https://www.tripadvisor.com). We use the Houyi crawler (http://www.houyicaiji.com) to extract three users' online reviews (including textual reviews, attribute-level ratings, overall ratings) about hotels on TripAdvisor.com, where each user published at least 100 comments during

Table 2. The number of valid online comments for each consumer and the proportion of different overall rating.

Name of consumer	Total number of valid online comments	The proportion of the different overall ratings				
		R-5	R-4	R-3	R-2	R-1
Dylan H	181	69.61%	23.20%	4.97%	2.22%	0.00%
Christopher N	122	65.83%	25.83%	7.50%	0.84%	0.00%
Nyc3kids	96	81.25%	8.33%	7.29%	0.00%	3.13%

Note. R-1→1-star rating; R-2→2-star rating; R-3→3-star rating; R-4→4-star rating; R-5→5-star rating.
Source: created by the authors.

Table 3. Attribute types and corresponding keywords extracted from textual reviews.

Attribute type	Keywords
Value	price, expense, cost, value, discount, money, paid, spend, worth, cheap, budget, affordable
Service	staff, manager, service, reception, shuttle, luggage, waitress, waiter
Food	breakfast, dinner, buffet, lunch, meal, pizza, beef, dish, meal, drink, coffee, tasting, tasty
Location	center, easy to find/go, station, locate, location, airport, place, spot, near, views, gem, occasion, convenient
Rooms	shower, pool, space, bath, soft, bar, facilities, lounge, decoration, wife, lift, stair, table, suite, toilet, tv
Cleanliness	clean, clear, neat, dirty, pillows, carpet, sheets, towel
Sleep quality	sleep, bed, quiet, noise, sleeping
Atmosphere	atmosphere, atmospheric, building, wall, experience, feel, lock, safe, safety, feeling, felt.

Source: created by the authors.

Table 4. An example of sentiment analysis based on the RNTN model.

Textual reviews	Food was decent, not amazing. We got a table on the roof which had nice views though the tables on the steps looked equally pleasant. Plaka is such an atmospheric area.
Keywords	food; views; table; atmospheric;
Attribute types	Food (t_1^1), Location (t_1^2), Rooms (t_1^3), Atmosphere (t_1^4)
Representation of PLTSs	$t_1^1 = t_1^2 = t_1^3 = \{0.014, 0.056, 0.123, 0.499, 0.308\}$ $t_1^4 = \{0.028, 0.145, 0.436, 0.357, 0.024\}$

Source: created by the authors.

the period from January 4, 2014 to December 10, 2021. A total of 407 online comments from three consumers are collected.

For all collected raw online reviews, we remove duplicate reviews, non-English reviews and uninformative reviews. In addition, we also filter out the reviews with mismatched overall ratings and attribute-level ratings, such as a review including an overall rating with two points but all the attribute-level ratings with four points. Finally, we obtain 399 online reviews of three consumers for data analysis. Table 2 shows the number of valid online comments for each consumer and the proportion of different overall ratings in online reviews. The statistical results show that all three consumers tend to give high overall ratings to different hotels.

According to the procedure of attribute extraction based on the LDA model and the sentiment analysis based on the RNTN model, we acquire the attribute types used for product evaluation by three consumers, and the attribute tendencies and intensities expressed in PLTSs of product attributes mentioned in textual reviews. Table 3 illustrates the product attribute types and corresponding keywords for three consumers. Table 4 represents an example of sentiment analysis using the RNTN model. For a given textual review in Table 4, three attributes, including food, location and rooms, are described by

Table 5. Frequency of different attribute types being commented in textual comments and attribute-level ratings.

Name of consumer	Attribute types							
	Value	Service	Food	Location	Rooms	Cleanliness	Sleep quality	Atmosphere
Dylan H	79.01%	84.53%	79.56%	65.75%	12.71%	9.39%	29.28%	53.04%
Christopher N	14.17%	21.67%	63.33%	25.00%	4.17%	6.67%	14.17%	12.50%
Nyc3kids	44.79%	48.96%	61.46%	61.46%	46.88%	10.42%	20.83%	39.58%

Source: created by the authors.

Table 6. Parameters of marginal value functions and marginal attribute values of ratings for different consumers.

	Learned parameters				Marginal attribute values				
Name of consumer	r_1	r_2	β_1	β_2	R-1	R-2	R-3	R-4	R-5
Dylan H	0.578	1.044	1.235	2.000	0.241	0.278	0.500	0.630	0.759
Christopher N	0.511	1.030	1.235	2.000	0.240	0.392	0.500	0.628	0.756
Nyc3kids	0.275	1.059	2.000	2.000	0.425	0.465	0.500	0.632	0.762

Note. R-1→1-star rating; R-2→2-star rating; R-3→3-star rating; R-4→4-star rating; R-5→5-star rating.
Source: created by the authors.

similar emotional words. Thus, the sentiment analysis results of these attributes are consistent, and the representation of PLTSs is also consistent. Note that if there are multiple descriptions of the same attribute in a textual comment, the sentiment analysis results of this attribute should take the average value of those descriptions.

After statistics, the frequency of various attributes being commented in textual comments and attribute-level ratings of three consumers can be seen in Table 5. For consumer Dylan H, four attributes including 'value', 'service', 'food' and 'location' are mentioned frequently in online comments, while for other two consumers, only the attribute 'food' is evaluated frequently.

4.2. The results of attribute value extraction

According to the calculation steps in Section 3.4, we extract attribute values from qualitative textual comments and quantitative attribute-level ratings of three consumers respectively, and then use the rules to integrate the extracted attribute values to obtain all attribute values of hotels corresponding to each consumer. Table 6 shows the learned parameters of marginal value functions used to characterize the attribute values of hotels corresponding to three consumers. The results in Table 6 show that different consumers have different evaluation benchmarks, that is, the same rating of an attribute has different marginal values for different consumers. For the three consumers, the marginal attribute values of the 2-star rating are significantly different. The attribute value of the 1-star rating given by consumer Nyc3kids is significantly higher than those of the other two consumers.

Considering that products with an overall rating of 5-rating have more advantages than products with an overall rating of no more than 3-rating, we compare the values of all products with an overall rating of no more than 3-rating aggregated by the ACI and those of the products with an overall rating of 5-rating, and take them as the input information of Model 2 one by one. When there is a feasible solution to Model 2, many sets

Table 7. The proportion of the top four in importance of each attribute type.

	Attribute types							
Name of consumer	Value	Service	Food	Location	Rooms	Cleanliness	Sleep quality	Atmosphere
Dylan H	11.45%	23.66%	44.27%	46.56%	58.02%	49.62%	49.62%	47.33%
Christopher N	61.29%	46.77%	43.55%	53.23%	41.94%	54.84%	40.32%	35.48%
Nyc3kids	41.46%	35.57%	39.20%	28.05%	40.24%	39.02%	42.68%	37.80%

Source: created by the authors.

Table 8. The distribution of the compensation degree.

Name of consumer	$\lambda<10$	$10<\lambda<10^3$	$10^3<\lambda<10^5$	$10^5<\lambda<10^7$	$10^7<\lambda<10^9$	$\lambda>10^9$
Dylan H	1	6	4	35	83	2
Christopher N	0	0	0	9	55	2
Nyc3kids	0	0	2	13	73	0

Source: created by the authors.

of fuzzy measure compatible with consumers' preferences and characters towards the compensation degree in aggregation can be gained, which is the same as the number of different products in the input information of Model 2. Once the infeasible solution appears in Model 2, we delete the entered pairwise preference comparison information until the feasibility is restored. Finally, we obtain 131, 62 and 82 sets of preference parameters compatible with the preference information of three consumers respectively.

Since we only consider the pairwise interactions between attributes, the Shapley values of attributes are computed to reflect the importance of a single attribute to consumers. We counted the top four attribute in each set of learned preference parameters, and then further calculated the proportion of each attribute ranked in the top four among all learned parameter results, as shown in Table 7. According to the results shown in Table 7, for the consumer Dylan H, although two attributes 'value' and 'service' are mentioned in many online comments shown in Table 5, he/she pays more attention to other attributes of hotels such as attributes 'Rooms', 'Cleanliness' and 'Sleep quality'. For consumer Christopher N, the attribute 'value' has a greater impact on him/her than the frequently mentioned attribute 'food'. For the third consumer Nyc3kids, although the proportion of attribute importance is different, the difference between the proportions is relatively small. That is, there is no attribute that the third consumer obviously pay attention to.

The results of three consumers' compensation attitude towards the aggregation process can be seen in Table 8. For different consumers, in all the obtained parameter results, the number of compensation degrees distributed in different ranges is different. Compared with the other two consumers, the consumer Dylan H has higher frequency of low values of the compensation degrees between attribute values. But overall, all consumers are highly likely to tolerate compensation between attribute values in the aggregation process.

We also make statistics on the proportion of possible positive and negative interactions between two attributes in all the learned preference parameters sets. The interaction results with a higher proportion are shown in Tables 9–11. For three consumers, although the degrees of interactions between different attributes are different, there is a great probability of negative effects between any two attributes. For the first consumer Dylan H, there is a high probability of negative interaction between

Table 9. The possible interactions with higher proportion between two attributes for the consumer Dylan H.

V-S	V-F	V-L	V-R	V-C	V-SQ	V-A
*79.39%	*76.34%	***80.92**%	*73.28%	*67.18%	*66.41%	*61.83%
S-F	S-L	S-R	S-C	S-SQ	S-A	F-L
*79.39%	*70.99%	*67.18%	*67.18%	*54.96%	*69.47%	*67.94%
F-R	F-C	F-SQ	F-A	L-R	L-C	L-SQ
*70.23%	*66.41%	*64.89%	*62.59%	*73.28%	*61.07%	*70.99%
L-A	R-C	R-SQ	R-A	C-SQ	C-A	SQ-A
*75.57%	*74.81%	*77.10%	*74.05%	*74.81%	***81.68**%	*71.76%

Note. * means that there is a negative interaction effect between two criteria; V→Value; S→Service; F→Food; L→Location; R→Rooms; C→Cleanliness; SQ→Sleep quality; A→Atmosphere.
Source: created by the authors.

Table 10. The possible interactions with higher proportion between two attributes for the consumer Christopher N.

V-S	V-F	V-L	V-R	V-C	V-SQ	V-A
*72.58%	*70.97%	*75.81%	*77.42%	*67.74%	*72.58%	*74.19%
S-F	S-L	S-R	S-C	S-SQ	S-A	F-L
***83.87**%	*72.58%	*72.58%	*62.90%	*79.03%	*74.19%	*70.97%
F-R	F-C	F-SQ	F-A	L-R	L-C	L-SQ
*79.03%	*70.97%	*77.42%	*72.58%	*83.87%	*74.19%	*64.52%
L-A	R-C	R-SQ	R-A	C-SQ	C-A	SQ-A
***83.87**%	***82.26**%	*69.35%	*66.13%	*74.19%	*79.03%	*69.35%

Note. * means that there is a negative interaction effect between two criteria; V→Value; S→Service; F→Food; L→Location; R→Rooms; C→Cleanliness; SQ→Sleep quality; A→Atmosphere.
Source: created by the authors.

Table 11. The possible interactions between eight attributes for the consumer Nyc3kids.

V-S	V-F	V-L	V-R	V-C	V-SQ	V-A
*71.95%	*75.61%	*78.05%	*78.05%	*70.73%	*73.17%	*71.95%
S-F	S-L	S-R	S-C	S-SQ	S-A	F-L
*71.95%	*74.39%	*74.39%	*75.61%	***80.49**%	*76.83%	*75.61%
F-R	F-C	F-SQ	F-A	L-R	L-C	L-SQ
*79.27%	*75.61%	*74.39%	*70.73%	*67.07%	*68.29%	*64.63%
L-A	R-C	R-SQ	R-A	C-SQ	C-A	SQ-A
*78.05%	*68.29%	*76.83%	*70.73%	*73.17%	***82.93**%	*73.17%

Note. * means that there is a negative interaction effect between two criteria; V→Value; S→Service; F→Food; L→Location; R→Rooms; C→Cleanliness; SQ→Sleep quality; A→Atmosphere.
Source: created by the authors.

two sets of attributes with respect to ‘value’ and ‘location’, ‘Cleanliness’ and ‘Atmosphere’. The negative interactions between attributes ‘service’ and ‘food’, attributes ‘location’ and ‘atmosphere’, and attributes ‘room’ and ‘cleanliness’ are also likely to occur in the aggregation process of consumer Christopher N. The two sets of negative interaction between attributes ‘service’ and ‘sleep quality’, and attributes ‘cleanliness’ and ‘atmosphere’ have a high probability in the process of consumer evaluation.

4.3. Discussion

The proposed method introduces the aggregation-disaggregation paradigm in NAROR into consumer preference analysis. We briefly explain the difference between our method and other techniques for consumer preference analysis.

The proposed approach is different from other techniques for consumer preference analysis as discussed by Li et al. (2020). Collaborative filtering-based techniques take the preferences of other consumers as a whole to predict target consumers' preferences based on consumer preference similarity. Content-based techniques focus on predicting preferences by observed product contents and consumer characteristics. While these two types of preference analysis methods take advantages of predicting the overall ratings of products that reflects the degree of consumer propensity for different products and making accurately recommendation, they do not provide insights on how a consumer evaluates a product and how much the consumer attaches importance to the features or attributes of the product. The proposed approach could be utilized to show a visualization of the marginal value function for each attribute in terms of attribute-level ratings and the global value function for the aggregation of attribute values. The parameters of the marginal value function corresponding to each consumer can be seen in Table 6. Due to limited space, we do not show all sets of the learned preference parameters but only give the distribution of these parameters. These learned parameters can support product/service managers to understand the attributes of a product that attract consumers most and how these attributes affect consumers' evaluation to different products/services. For example, by collecting the historical comments of consumer Dylan H for consumer preference analysis, the platform manager can understand that this consumer often mentions several attributes such as value, service and food in his/her comments, but what can more affect his/her evaluations about a hotel are attributes such as room, cleanliness and sleep quality, and for this consumer, there is a high feasibility of negative interactions among these three important attributes. If a hotel has a good performance in attributes including room, cleanliness and sleep quality, even if the performance in attributes service and food are not so good, the consumer Dylan H may give the hotel a high overall rating. But, if the price of the hotel is very high, it will affect the evaluation behavior of this consumer and lead him/her not to give the hotel a high rating.

Compared with existing MADM approaches for consumer preference analysis, the proposed approach has characteristics that have not yet been reflected in other literature. First, the proposed approach identifies different attribute types and values by considering both textual reviews and attribute-level ratings. As described in the part of problem description, reviews of products with respect to several attributes may be post in different place. The separate use of attribute-level ratings or textual reviews may cause the incomplete information extraction about the evaluation values of product attributes in terms of types and values. However, existing literature using MADM methods for consumer preference analysis did not discuss this problem, which can be seen in Table 12. Moreover, the proposed approach conducts consumer preference analysis based on individual consumers' online comments, and aims to extract individual consumers' preference parameters with respect to the importance of attributes, the interactions between pairwise attributes, and the tolerance of consumers to make compensation between attribute values. Guo et al. (2020) extracted attribute types and calculated the importance of attributes by combining textual reviews and overall ratings of group consumers, and then extracted consumers' preference structure based on an additive value function. Considering the influence of time period, Zhu et al.

Table 12. The difference between the existing consumer preference analysis from MCDM and the proposed method.

		Online reviews				The extracted results in global value function			
Reference	The context of consumer preference analysis	The use of textual reviews	The use of attribute-level ratings	The use of overall ratings	The marginal value function	The importance of attribute	The interaction between attributes	The individual consumers' compensation attitude	The property of consumers
Guo et al. (2020)	online reviews	✓	×	✓	✓	✓	✓	×	Group consumers
Zhu et al. (2022)	online reviews	✓	×	✓	–	✓	✓	×	Individual consumers
Branke et al. (2016); Liu et al. (2019, 2021)	MCDM	×	×	×	✓	✓	✓	×	Either group consumers or individual consumers
Wu and Liao (2021a)	online reviews	✓	✓	×	✓	×	×	×	Individual consumers
The proposed method	online reviews	✓	✓	✓	✓	✓	✓	✓	Individual consumers

Note. '✓'means the tool was applied; '×'means the tool was not applied; '-' means the tool was not discussed.
Source: created by the authors.

(2022) used textual reviews to extract attribute types, and analyzed individual consumers' preference based on an additive value function. These two approaches did not discuss the interactions between attributes and the personalized tolerance of individual consumers for compensation between attribute values. Wu and Liao (2021a) constructed a personalized marginal value function from the perspective of individual consumers, and used the relations between text comments and attribute-level ratings to obtain the unknown preference parameters. Nevertheless, this study did not discuss how to extract individual consumer preferences from the global value function. Other studies (Branke et al., 2016; Liu et al., 2019, 2021) constructed nonlinear programming with a complex value function as preference model to extract consumers' preferences, which can derive the importance of attributes and the interaction between attributes. But these studies were not applied in the context of consumer preference analysis based on online comments.

The objective of this study is to provide product/service managers with consumer preference information rather than directly serving consumers. For managers, they can utilize the historical data of reviewers with relatively large volume of reviews on the platform to extract their individual preferences, and recommend products/services to reviewers according to the obtained consumer preferences so as to acquire more benefit.

It is worth noting that the method of extracting attribute types and attribute values in this paper is suitable for websites with three kinds of online comments at the same time, but it does not mean that the data extracted from other websites cannot be used for consumer preference analysis. As long as attribute types and attribute values can be obtained, consumer preference analysis can be conducted according to the preference extraction process presented in this study.

5. Conclusion

Due to the characteristics of being publicly available and easily collected, online review is a kind of emerging information resource for firms to monitor and manage the preferences of consumers. If attribute types, attribute values and overall consumer satisfaction can be measured from a huge amount of online reviews, then the importance of attributes and the interactions between pairwise attributes can be obtained for different products/services considering different periods. Inspired by this idea, this paper utilized both textual reviews and attribute-level ratings to extract attribute types based on the LDA model, and obtained the possible sentiment tendencies and their probability distribution concerning each attribute based on the RNTN model. The attribute values of each attribute in textual reviews were further obtained by the expectation function of PLTSs. Attribute values with respect to attribute-level ratings were determined by a linear programming model based on the mixed exponential function. To reduce the workload of consumers, an aggregation-disaggregation paradigm in NAROR was introduced into the ACI model to extract individual preference information from online reviews. The results of case study showed that parameters including the importance of attributes, interactions between attributes, and individual attitudinal characters towards the compensation in the aggregation process can be learned by our proposed method. In this way, product/service managers can know more consumer preferences and satisfaction over products/services and further recommend products/services to consumers pertinently.

We envisage further research in other directions. First, the key challenge of consumer preference analysis based on the value-driven method comes down to predefine a reasonable aggregation function. The future study may pay more attention to detect the preferences of customers based on other value functions. Moreover, more complex natural language and sentiment analysis techniques can be applied to extract attribute types and attribute values. Considering that the more the number of attributes is, the more complex the model is, the hierarchical structure and heuristic algorithms can be designed to optimize the computation of interactions between attributes.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. http://tripadvisor.com/
2. An intolerant or perfectionist DM requires the performances of all the given criteria to be good and cannot accept the bad performances of some criteria are compensated by the good performances of other criteria.
3. A tolerant DM accepts that only the performances of some criteria are good and the bad performances on other criteria are compensated to
4. Since
$$\min\{f(c_j)|j \in T\} = \eta,$$
$$\log_\lambda(\sum_{T\subseteq C} m^\mu(T)\lambda^{\min\{f(c_j)|j\in T\}} = \log_\lambda(\lambda^\eta \sum_{T\subseteq C} m^\mu(T)) = \log_\lambda(\lambda^\eta) + \log_\lambda(\sum_{T\subseteq C} m^\mu(T)) = \eta.$$
5. The uninformative reviews mean the words or sentences in online textual reviews that have nothing to do with products/services.
6. The inconsistent reviews refer to the description of product/service performance obtained from textual comments that is inconsistent with the overall ratings or attribute-level ratings of the product/service given by consumers. For example, the description of a product in textual comments is good and positive, but it gets a very low overall rating.
7. It means that the attribute value with a price of 100 and that with a distance of 10 kilometers cannot be directly combined or compared.

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