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An integrated method for product ranking through online reviews based on evidential reasoning theory and stochastic dominance

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A B S T R A C T

Online reviews play an important role in consumers' purchasing decisions. However, many online reviews confuse consumers when they wish to make a purchase but lack experience. To solve the problem of product ranking based on online reviews, two important issues must be addressed: sentiment analysis and product ranking based on multi-criteria decision-making (MCDM) methods. Therefore, this paper proposes an integrated MCDM method for product ranking through online reviews based on evidential reasoning (ER) theory and stochastic dominance (SD) rules. First, online reviews are preprocessed to obtain product attributes and weight values. Then, we use naive Bayes (NB), logistic regression (LR), and support vector machines (SVM) for the sentiment analysis of online reviews, and the results of the three classifiers are aggregated using ER theory. In addition, according to the confidence distribution matrix of sentiment orientations, SD rules are used to determine the stochastic dominance relations between pairwise alternatives for each attribute. Furthermore, we use the stochastic multi-criteria acceptability analysis (SMAA)-PROMETHEE method to obtain the final product ranking results and conduct sensitivity analysis. Finally, a case study on ranking computer products from JD Mall through online reviews is provided to illustrate the validity of the proposed method.

1. Introduction

With the rapid development of Internet technology and the popularization of e-commerce platforms, public consumption has gradually become networked and informationally oriented, and numerous online reviews are posted on the Internet every day [1,2]. Online reviews as a data source can be used for different data analysis problems, such as customer satisfaction modeling [3], product ranking [4–6], and product sales forecasting [7–9], among others. For online shopping, consumers who have already purchased products online share information about their purchased products on e-commerce platforms, while potential consumers can browse online reviews about alternative products and make purchasing choices. Therefore, online reviews can not only help consumers fully understand the authenticity of the product information; they can also directly or indirectly influence the purchasing behaviors of potential consumers. Today, there are many e-commerce

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platforms and review websites, including Amazon (http://www.amazon.com/), JD Mall (https://www.jd.com/), Autohome (https://www.autohome.com/), and Yelp (http://www.yelp.com/). However, due to the excessive number of online reviews, potential consumers are often unable to make decisions quickly and effectively. Therefore, the product ranking problem through online reviews is a popular topic for research and has extensive theoretical and practical significance.

The problem of product ranking through online reviews has received comprehensive attention from many scholars, and numerous methods have been proposed [4–6,10]. To better understand the research process for this area, we use VOSviewer software (https://www.vosviewer.com) to map the co-occurrence network based on the existing literature discussing the problem of product ranking through online reviews, as shown in Fig. 1 (with number of occurrences of keywords $\geqslant 3$). According to Fig. 1, we can see that there are many topics that involve an extension of this issue, such as sentiment analysis, product recommendation, review helpfulness, etc. At present, most research findings divide the product ranking problem into two steps: The first step is to analyze the sentiment orientations of online reviews, while the second step is to rank products based on multi-criteria decision-making (MCDM) methods, as shown in Fig. 2. Recently, Fan et al. [11] reviewed the existing processes and methods of each stage in the product ranking problem, pointing out several promising research issues and future directions. In addition, currently, the sentiment analysis methods of online reviews are mainly divided into two categories [11]: **(1)** lexicon-based sentiment analysis and **(2)** analysis based on machine learning. Regarding the first category, Khoo et al. [12] presented a new general-purpose sentiment lexicon for the sentiment categorization of review texts. Further, Liu et al. [4] developed an identification algorithm based on sentiment dictionaries to identify the sentiment orientations of online reviews. Fu et al. [13] proposed an unsupervised approach to automatically discover these aspects in Chinese social reviews and sentiment orientations by applying the latent Dirichlet allocation (LDA) model and HowNet lexicon. As for the second category, Pang et al. [14] applied machine learning methods to conduct sentiment analysis, and the results obtained by using support vector machine (SVM) have the best classification effect. Likewise, Mohaiminul et al. [15] examined different methods of using machine learning algorithms for sentiment analysis with the aid of online reviews. Table 1 shows a comparison of these different approaches in terms of sentiment analysis.

Regarding product ranking, Nowak [16] proposesd a method to solve the stochastic MCDM problem based on stochastic dominance (SD) rules. This method determines the dominance relations between alternatives for each attribute based on SD rules. Then, according to the predefined preference thresholds, the preference relation between each pair of alternatives for each attribute is determined, and the ELECTRE-III method is used to calculate the ranking of all alternatives. To estimate the degrees of SD relation between pairwise alternatives, Zhang et al. [17] proposed a novel concept of the stochastic dominance degree (SDD) based on SD rules. By calculating the SDD, the SDD matrix is established, which represents the pairwise comparison of alternatives for each attribute. Then, based on the overall SDD matrix, the PROMETHEE-II method is used to calculate the product ranking results. Based on this, Tan et al. [18] presented the definition and related analysis of the prospect

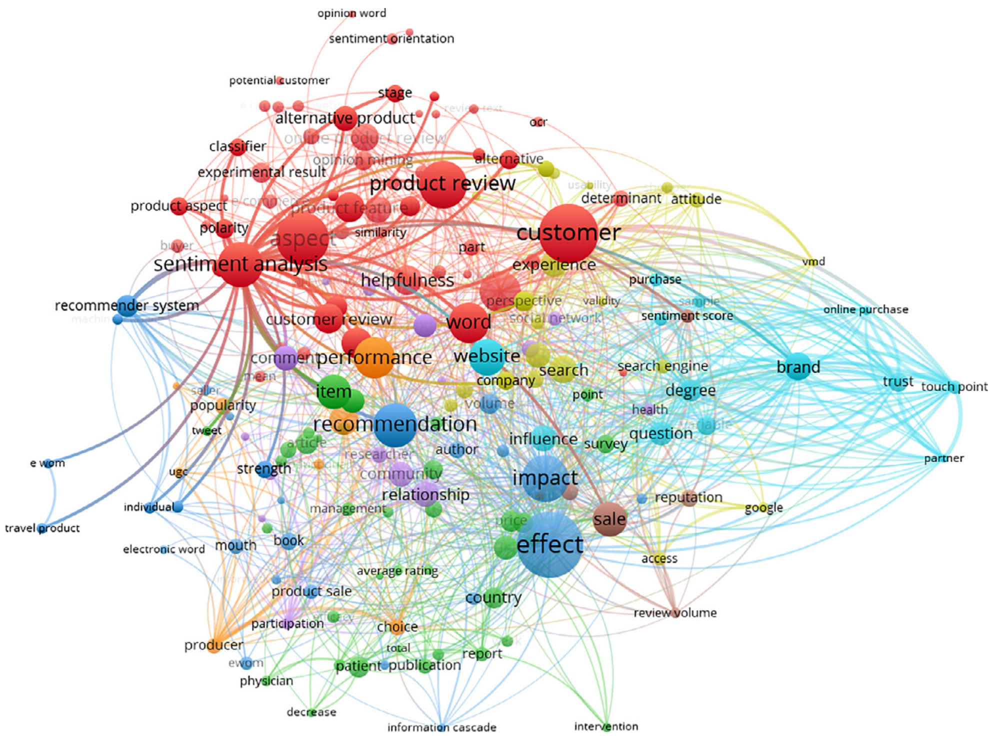


Fig. 1. A co-occurrence network for the product ranking problem.

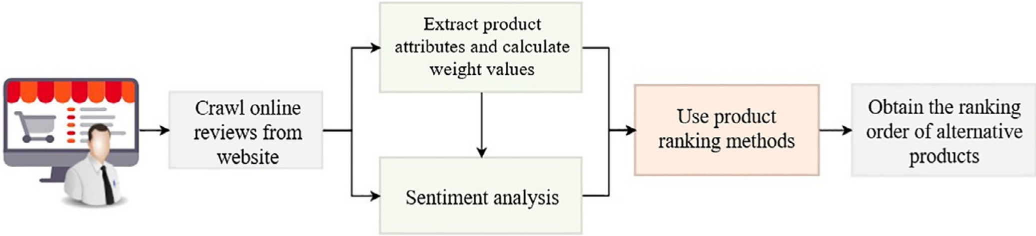


Fig. 2. The solution process of the product ranking problem based on online reviews.

Table 1
Comparison of methods for sentiment analysis.

Approaches	Advantages	Disadvantages	Computational time	Accuracy
NB	• Easy to implement. • Less sensitive to missing data.	• Based on the assumption that features are independent of each other.	Low	Good
LR	• Good mathematical properties. • Output in the form of probabilities.	• Less effective for dealing with data imbalances.	Low	Medium
SVM	• Computational complexity depends on the number of support vectors rather than the dimensionality of the sample space. • Good robustness.	• Difficult to implement for large-scale training samples.	High	Good
ME	• Flexible for setting constraints.	• The iterative process is computationally intensive. • Tends to overfit.	High	Medium
Lexicon-based	• Easy to understand and implement.	• High manual workload. • Limited by the quality of the emotional lexicon.	Low	Good
Deep neural networks	• Consider semantic features. • Good generalization ability.	• Poor model interpretability. • Require large-scale training samples.	Very high	Good

where NB, LR, and ME indicate naive Bayes, logistic regression, and maximum entropy, respectively.

Table 2
Other research processes for the product ranking problem.

	Data source	Attributes and weights	Sentiment analysis	Ranking process
Liu et al. [4]	Autohome	• Subjectively given.	• HowNet lexicon-based approach.	• Intuitionistic fuzzy weighted averaging operator and PROMETHEE-II.
Liu et al. [10]	Autohome	• Subjectively given.	• An algorithm based on SVM and the OVO strategy.	• Interval-valued intuitionistic fuzzy TOPSIS.
Fan et al. [20]	Automobile Home	• Subjectively given.	• Not mentioned	• SD rules and PROMETHEE-II.
Bi et al. [5]	Autohome	• Subjectively given.	• Representing sentiment analysis results using interval type-2 fuzzy numbers.	• Ranking per the closeness of each alternative product to the ideal product.
Wu et al. [21]	Amazon	• Not mentioned.	• Determined by rating stars.	• A hybrid MCDM process.
Zhang et al. [22]	TMALL	• Subjectively given attributes and objectively calculated weights.	• Representing sentiment scores by hesitant fuzzy set.	• Extended TODIM based on the 2-addictive fuzzy measure and Choquet integral.
Guo et al. [23]	Autohome	• LDA topic model.	• Not mentioned.	• Improved PageRank algorithm.

SDD (PSDD) in conjunction with prospect theory. Moreover, Jiang et al. [19] proposed a method of stochastic multi-attribute decision making (MADM) based on SD and almost stochastic dominance (ASD) rules, using ASD rules as supplements of SD rules to identify the dominance relations between alternatives. Table 2 summarizes the process of studies on the problem of product ranking in the selected literature.

According to the analysis mentioned above, existing studies have made significant contributions to the product ranking problem. However, there are still a few limitations, which can be summarized as follows:

- For the problem of product ranking, most previous studies ignore the steps of extracting attributes and calculating weights. They just use the subjective evaluation attributes and weights that the decision-maker provides to conduct subsequent analysis, which inevitably affects the reasonableness of the ranking results.
- As for the sentiment analysis of online reviews, most existing studies only discuss the positivity and negativity of the review texts and rarely discuss their neutrality. In addition, the accuracy of sentiment classification is very limited. How to integrate the classification results for the ranking process also needs to be considered.
- Previous studies only introduce SD rules to make pairwise comparisons between products and rank them using outranking methods. However, they do not consider the influence of parameter changing in the whole ranking process. In addition, few studies provide a complete framework of the product ranking problem based on online reviews, i.e., a combination of sentiment analysis and MCDM methods to rank online products.

Therefore, to overcome these limitations, the aim of this study is to propose an integrated method based on a combination of sentiment analysis and MCDM methods for product ranking through online reviews. To the best of our knowledge, evidential reasoning (ER) theory is widely used in information fusion problems. For example, Xu et al. [24] pointed out that ER theory can provide an effective mechanism to reduce the inaccuracy of classification. Through the improvement of Dempster combination rules, they propose a new classification process based on ER rules. In addition, many studies apply ER theory to cases of random uncertainty [25] and fuzzy uncertainty [26]. Thus, we introduce ER theory to combine the sentiment classification results of machine learning, which is a data-driven decision analysis method. For the process of product ranking, this is essentially an MCDM process of determining the dominance relations between alternatives. Furthermore, SD is a classic concept for comparing uncertain prospects [27]. Graves et al. [28] compared the six decision-making methods and concluded that SD is recommended because it requires the least restrictive assumptions. However, most preference relations can be identified via SD rules, but in incomparability situations, it is necessary for us to clarify the decision-maker's preference function [29]. We, thus, propose a combination of SD rules and the PROMETHEE method to measure preference information. Moreover, stochastic multi-criteria acceptability analysis (SMAA) is a good tool to measure the ranking of each alternative under a variety of preferences [30].

Thus, the main contributions of this paper can be summarized as follows:

- To objectively extract evaluation attributes and determine weights from online reviews, we propose a novel method based on the TextRank algorithm, which is more user-friendly for decision-makers who lack experience and knowledge.
- In terms of sentiment analysis, this paper proposes a combinatorial optimization method based on machine learning and ER theory for the sentiment analysis of online reviews. Using NB, LR, and SVM as classifiers, online reviews are classified into three sentiment levels: positive, neutral, and negative. Then, we use ER theory to aggregate the final sentiment classification results of the three classifiers, which can reduce the inaccuracy of the classification.
- For ranking problems, we propose an approach involving the use of SD rules for determining the SD relations between each pair of products in combination with the PROMETHEE method to calculate the final product ranking order, which can allow us to obtain more reasonable results. Moreover, we propose an SMAA-PROMETHEE method to complete the sensitivity analysis of preference thresholds and weights.

The remainder of this paper is organized as follows: Section 2 briefly introduces the basic concepts of ER theory and SD rules. Section 3 provides the procedures of the proposed method in detail, including sentiment analysis and the ranking process. In Section 4, a case study on ranking computer products from JD Mall is provided to illustrate the validity of the proposed method. Finally, Section 5 summarizes the main contributions and limitations of this paper and points out future research directions.

2. Preliminaries

In this section, we briefly introduce some basic concepts related to ER and SD, which are used throughout the paper.

2.1. Evidential reasoning

ER theory is a well-known uncertain reasoning method that Yang et al. [31] originally proposed to solve the defects of traditional Dempster-Shafer (DS) rules [32,33]. In essence, it is an extension of probability theory, as it assigns a basic probability distribution function to each power set space of basic events [34–36]. The definitions of ER rules are shown as follows.

Definition 1. [33] If $\Theta = \{H_1, H_2, \ldots, H_N\}$ is a finite and complete set composed of N pairwise mutually exclusive elements, where H_n is the n-th element in Θ. This is referred to as a frame of discernment. The set of all subsets in Θ is called the power set of Θ, and there are 2^n elements in the power set, which is denoted as:

$$2^{\Theta} = \{\phi, \theta_1, \theta_2, \ldots, \theta_N, \theta_1 \cup \theta_2, \theta_1 \cup \theta_3, \ldots, \Theta\}. \tag{1}$$

Definition 2. [33] Let Θ be a frame of discernment, then 2^{Θ} constitutes a set of propositions. Let A be a subset of $\Theta, \forall A \subseteq \Theta$, then basic probability assignment (BPA) can be defined as $m : 2^{\Theta} \rightarrow [0, 1]$, which satisfies the conditions:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1, \end{cases} \tag{2}$$

where $m(A)$ is the basic probability assignment value of proposition A, which is regarded as the reliability assigned to A accurately. If $m(A) > 0$, then A is called the focal element of the BPA function on Θ.

Definition 3. [31] Let $\beta_{n,i}$ be the confidence that the piece of evidence e_i $(i = 1, 2, \ldots, L)$ is rated as H_n, then the confidence distribution can be expressed as:

$$S(e_i) = \{(H_n, \beta_{n,i}) | n = 1, 2, \ldots, N;\ i = 1, 2, \ldots, L\}. \tag{3}$$

If the confidence distribution is complete, then $\sum_{n=1}^{N} \beta_{n,i} = 1$, otherwise $\sum_{n=1}^{N} \beta_{n,i} < 1$.

Definition 4. [35] Let $m_{n,i}$ be the basic probability assignment value of e_i, which is rated on H_n, and let $m_{H,i}$ represent the remaining basic probability value that has not been assigned to any level:

$$m_{n,i} = w_i \beta_{n,i}, \tag{4}$$

$$m_{H,i} = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w_i \sum_{n=1}^{N} \beta_{n,i}, \tag{5}$$

where w_i is the weight of e_i and meets $w_i \geqslant 0, \sum_{n=1}^{L} w_i = 1$. Here, $m_{H,i}$ can be divided into two parts defined as:

$$m_{H,i} = \tilde{m}_{H,i} + \bar{m}_{H,i}, \tag{6}$$

$$\bar{m}_{H,i} = 1 - w_i, \tag{7}$$

$$\tilde{m}_{H,i} = w_i \left(1 - \sum_{n=1}^{N} \beta_{n,i}\right). \tag{8}$$

Definition 5. [35] Let m_n be the result of combining the probability distribution of e_i and e_j, then the ER rules are shown as follows:

$$K = \left[1 - \sum_{t=1}^{N} \sum_{l \neq t}^{N} m_{t,i} m_{l,j}\right]^{-1}, \tag{9}$$

$$\{H_n\} : m_n = K\left[m_{n,i} m_{n,j} + m_{H,i} m_{n,j} + m_{n,i} m_{H,j}\right], \tag{10}$$

$$\{H\} : \tilde{m}_H = K\left[\tilde{m}_{H,i} \tilde{m}_{H,j} + \tilde{m}_{H,i} \bar{m}_{H,j} + \bar{m}_{H,i} \tilde{m}_{H,j}\right], \tag{11}$$

$$\bar{m}_H = K\left[\bar{m}_{H,i} \bar{m}_{H,j}\right], \tag{12}$$

where K represents the degree of conflict between the pieces of evidence. When all of the pieces of evidence are combined, $\bar{m}_H$ is then assigned to each level according to the following rule:

$$\{H_n\} : \beta_n = \frac{m_n}{1 - \bar{m}_H}, \quad n = 1, 2, \ldots, N. \tag{13}$$

A simple numerical example is shown to illustrate the computational process of ER theory.

Example 1. Suppose that $\Theta = \{H_1, H_2, H_3\} = \{negative, neutral, positive\}$ and there are two pieces of independent evidence, e_1 and e_2. The corresponding confidence distributions assigned by e_1 and e_2 can be expressed as: $S(e_1) = \{(H_1, 0.3), (H_2, 0.2), (H_3, 0.5)\}$ and $S(e_2) = \{(H_1, 0.2), (H_2, 0.5), (H_3, 0.3)\}$. Additionally, $w_1 = 0.6$ and $w_2 = 0.4$ are weights of e_1 and e_2, respectively. According to ER theory, the combination results of e_1 and e_2 are presented in Table 3.

From Table 3, ER theory comprehensively considers the confidence distribution ofpieces of evidence e_1 and e_2. However, this is just a simple example to illustrate the process of evidence combination, which is different from simple weighted calculation. ER theory is considered as a generalized Bayesian reasoning process [36].

Table 3
The computational process of ER theory for **Example 1**.

	e_1	e_2	$m_{n,1}$	$m_{n,2}$	$m_{H,1}$	$m_{H,2}$	K	m_n	$\bar{m}_H$	β_n
H_1	0.3	0.2	0.18	0.08				0.185		0.260
H_2	0.2	0.5	0.12	0.20				0.211		0.296
H_3	0.5	0.3	0.30	0.12				0.316		0.444
Θ					0.4	0.6			0.288	
w	0.6	0.4					1.198			

2.2. Stochastic dominance

Some definitions of SD rules are introduced as follows, where FSD, SSD, and TSD denote the first degree, second degree, and third degree of SD, respectively.

Let a and b $(a < b)$ be two real numbers. X_1 and X_2 are two random variables on interval $[a, b]$. Let $F_1(x)$ and $F_2(x)$ be the cumulative distribution functions of X_1 and X_2.

Let $I_1(x) = F_1(x) - F_2(x), I_2(x) = \int_a^x I_1(y)dy$, and $I_3(x) = \int_a^x I_2(t)dt$.

Definition 6. [37] X_1 dominates X_2 by the first degree (denoted as $X_1\text{FSD}X_2$) if and only if $F_1(x) \neq F_2(x)$ and $I_1(x) = F_1(x) - F_2(x) \leqslant 0$ for all $x \in [a, b]$.

Definition 7. [37] X_1 dominates X_2 by the second degree (denoted as $X_1\text{SSD}X_2$) if and only if $F_1(x) \neq F_2(x)$ and $I_2(x) = \int_a^x I_1(y)dy \leqslant 0$ for all $x \in [a, b]$.

Definition 8. [38] X_1 dominates X_2 by the third degree (denoted as $X_1\text{TSD}X_2$) if and only if $F_1(x) \neq F_2(x), I_3(x) = \int_a^x I_2(t)dt \leqslant 0$, and $E_1(x) \geqslant E_2(x)$ for all $x \in [a, b]$, where $E_1(x)$ and $E_2(x)$ are mathematical expectations of X_1 and X_2, respectively.

According to the above SD rules, several interesting properties are shown as follows.

Remark 1. (*Asymmetry*) If there is $F_1(x)$ FSD $F_2(x), F_1(x)$ SSD $F_2(x)$ or $F_1(x)$ TSD $F_2(x)$, then there is no $F_2(x)$ FSD $F_1(x), F_2(x)$ SSD $F_1(x)$, or $F_2(x)$ TSD $F_1(x)$.

Remark 2. (*Transitivity*) If there is $F_1(x)$ FSD $F_2(x)$ and $F_2(x)$ FSD $F_3(x)$, then $F_1(x)$ FSD $F_3(x)$, which is the same for SSD and TSD.

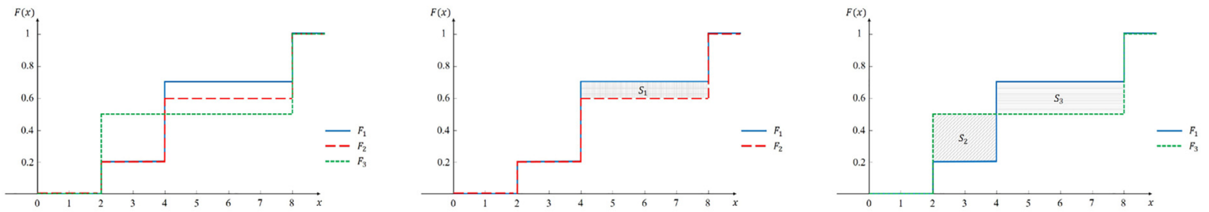
According to the SD rule, FSD requires that the two cumulative distribution functions being compared do not cross but can be tangent to each other. The SSD integral condition, $I_2 \leqslant 0$, implies that up to each point x, the area enclosed between the two distributions under consideration should be non-negative. Furthermore, the preference of one alternative over another for TSD may be due to its higher mean and positive skewness. For a better understanding of this, in what follows, we use an example to illustrate the definition of SD rules.

Example 2. Suppose that there are three alternatives (A_1, A_2, A_3), then the evaluated probabilities under different returns are shown in Table 4, where x denotes the return value.

According to the data in Table 4, we plot the cumulative distribution function of the three alternatives for the returns, as shown in Fig. 3(a), where F_1, F_2, and F_3 correspond to the cumulative distribution functions of A_1, A_2, and A_3, respectively. Additionally, the three alternatives are compared in pairs, as shown in Fig. 3(b) and (c), where S_1 denotes the accumulated area between the curves for $F_1(x)$ and $F_2(x)$ under the curve for $F_1(x); S_2$ denotes the accumulated area between the curves for $F_1(x)$ and $F_3(x)$ under the curve for $F_3(x); S_3$ denotes the accumulated area between the curves for $F_1(x)$ and $F_3(x)$ under the curve for $F_1(x)$. Based on Definitions 6–8 and the size of the area of S_i (i = 1,2,3), we can obtain the SD relation between the alternatives as follows: $A_1\text{TSD}A_3, A_2\text{FSD}A_1$, and $A_2\text{SSD}A_3$. More specifically, in this example, the pairwise dominance

Table 4
Distributional evaluations of the three alternatives.

Returns	Alternatives		
	A_1	A_2	A_3
2	0.2	0.2	0.5
4	0.5	0.4	0
8	0.3	0.4	0.5



(a) Cumulative distribution functions for three alternatives (b) Cumulative distribution functions F_1 and F_2 (c) Cumulative distribution functions F_1 and F_3

Fig. 3. Cumulative distribution function graphs for **Example 2**.

relations among the three alternatives can be obtained according to the SD rules; that is, A_2 is the best, followed by A_1. However, when faced with more complex situations, the dominance relations among all alternatives cannot be obtained based only on the SD criterion.

3. The proposed method

In this section, motivated by the idea of combinatorial optimization, we propose an integrated method based on ER theory and SD for product ranking through online reviews. The procedure is shown in Fig. 4. Firstly, we provide the notations that are used throughout this study in Table 5.

3.1. Crawling and preprocessing online reviews

Before conducting sentiment analysis, the crawled online reviews need to be preprocessed. The specific steps are as follows.

3.1.1. Acquiring online reviews

Nowadays, numerous online reviews of products and services are posted on e-commerce platforms such as Amazon (http://www.amazon.com/), JD Mall (https://www.jd.com/), and Autohome (https://www.autohome.com/). In this study, we use Bazhuayu crawler software (https://www.bazhuayu.com/) to obtain the review data of computer products from the JD Mall website (https://www.jd.com/). Bazhuayu crawler software is an easy-to-use big data crawling tool that analyzes the request and response rules of a website. Here, let $\mathbb{D} = \{D_1, D_2, \ldots, D_R\}$denote the set of crawled online reviews, where D_r is the r-th review ($r = 1, 2, \ldots, R$).

3.1.2. Segmenting words and tagging parts-of-speech

Word segmentation is the process of using specific rules and algorithms to segment complete sentences into individual word sequences. Word segmentation plays an important role in data processing, including in information retrieval and information filtering. At present, common text processing tools include ICTCLAS and jieba, SnowNLP, pynlpir components in Python, etc. In this paper, the jieba tool is used to segment Chinese texts and tag parts-of-speech, which can be imported via Python. For example, preprocessing the review "*Appearance: very beautiful and good shape*", we can obtain the result "*Appearance/n: /w very/d pretty/a, /w and/c good/a shape/n*", where "/n" means noun, "/w" means punctuation, "/d" means adverb, "/a" means adjective, and "/c" means conjunction.

3.1.3. Stop word removing

Stop words refer to words that carry little useful information in a text. By removing stop words, the efficiency of text analysis can be improved. Stop words can generally be summarized into two categories: (1) words without any emotional information, such as "of", "this", "the", etc.; (2) punctuation marks, logical characters, and special characters, such as commas, parentheses, line breaks, etc. Take the same comment above as an example, we get the result "*Appearance/ very/ beautiful/ good/ shape*" after deleting the stop words.

3.1.4. Extracting attributes and determining weights

There have been many studies on attribute extraction methods [13,23]. For example, Bouyssou [39] points out that a set of attributes in the MCDM problem should satisfy exhaustiveness; that is, the attributes should cover the decision-maker's comprehensive evaluation of the problem. Extracting evaluation attributes from online reviews requires the use of the methods of natural language processing. The TextRank algorithm is a graph-based ranking algorithm for text [40]. By segmenting the text into phrase units, a node connectivity graph is constructed. The important elements are extracted from the text using features such as word and phrase frequencies, and the TextRank values of the phrases are calculated via iterations.

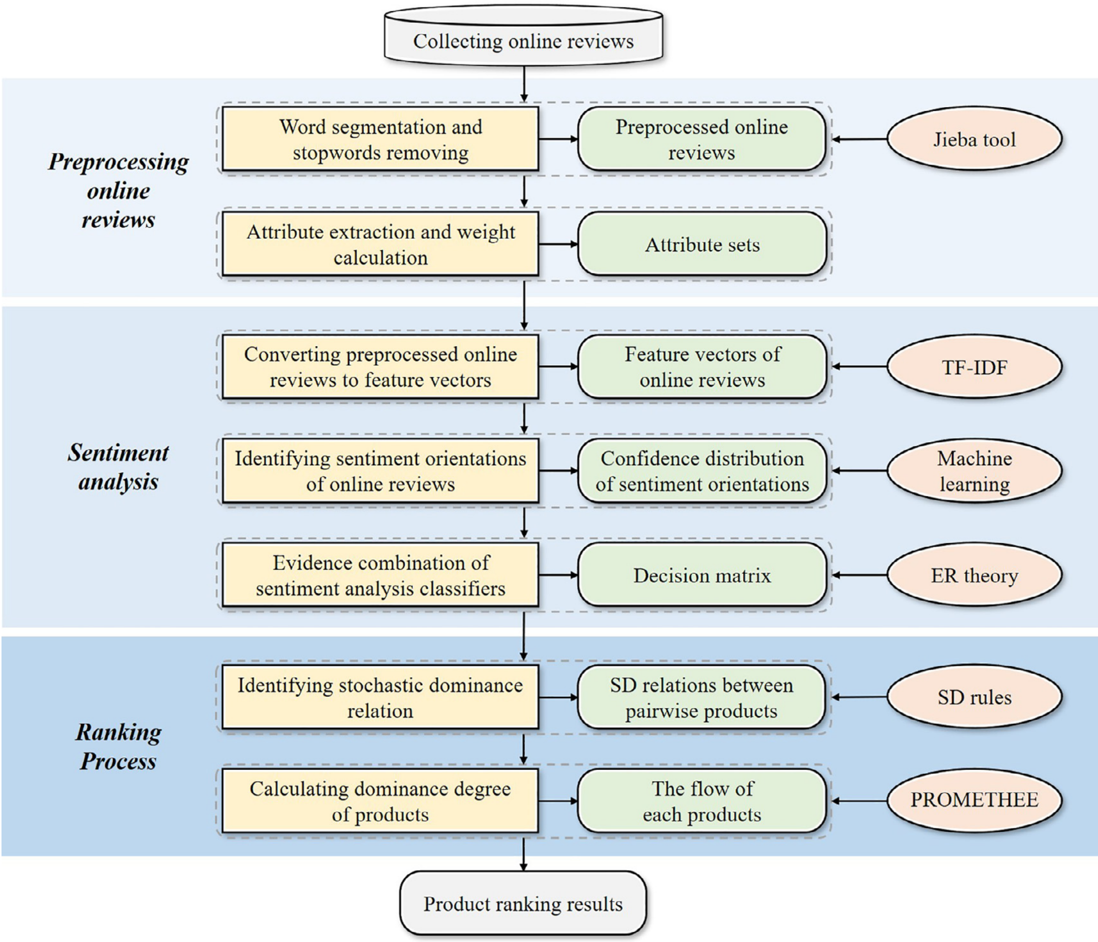


Fig. 4. Our proposed method for the product ranking problem.

Table 5
Notations and explanations.

Notations	Explanations
$A = \{A_1, A_2, \ldots, A_m\}$	A set of m alternative products, where A_i represents the $i-th$ alternative product, $i = 1, 2, \ldots, m$.
$C = \{C_1, C_2, \ldots, C_n\}$	A set of n attributes, where C_j represents the $j-th$ attribute, $j = 1, 2, \ldots, n$.
$w = \{w_1, w_2, \ldots, w_n\}$	A set of n weights, where w_j represents the objective weight of attribute C_j and satisfies $w_j \geqslant 0$, $\sum_{j=1}^{n} w_j = 1$.
$\Theta = \{S_1, S_2, S_3\}$	A frame of discernment, where S_1, S_2, and S_3 represent negative, neutral, and positive sentiment orientations, respectively.
ζ_{ij}	The evaluation level of product A_i for attribute C_j.
$F_{ij}(x)$	The cumulative distribution function of the evaluation level.
$\overline{\mathrm{SD}}$	SD relations between products, $\overline{\mathrm{SD}} \in \{\mathrm{FSD}, \mathrm{SSD}, \mathrm{TSD}\}$
e_{ij}	A mathematical expectation of the evaluation level ζ_{ij}.
$P_j(A_i, A_k)$	The priority degree of product A_i compared to product A_k for attribute C_j.
$P(A_i, A_k)$	The overall priority degree of product A_i compared to product A_k.
$\phi^+(A_i)$	The positive flow of product A_i.
$\phi^-(A_i)$	The negative flow of product A_i.
$\phi(A_i)$	The net flow of product A_i.

Finally, the phrases with high-ranking values are selected for summarizing the content of the text. For online reviews, the TextRank algorithm considers the characteristics of semantics and context, making it more suitable for the analysis of a short text. At present, the jieba tool is available to implement TextRank in the Python programming environment.

However, the attributes extracted by the TextRank algorithm only establish the initial attribute set, which needs to be further summarized and classified through manual screening. Let $T_j = \{T_{j1}, T_{j2}, \ldots, T_{jL}\}$ denote the set of synonyms of attribute C_j, where T_{jl} denotes the l-th synonym of attribute C_j ($l = 1, 2, \ldots, L$). Additionally, let T_j^r denote whether the attribute C_j or its synonyms appear in the r-th review ($r = 1, 2, \ldots, R$). If it appears, then $T_j^r = 1$, otherwise $T_j^r = 0$.

For e-commerce products, the more times an attribute is mentioned in online reviews, the more important the attribute is as a measurement standard, so attribute weight has an important impact on the final product ranking results. Therefore, objectively, the importance of attributes is calculated using:

$$w_j = \frac{\sum_{r=1}^{R} T_j^r}{\sum_{j=1}^{n}\sum_{r=1}^{R} T_j^r}, \quad j = 1, 2, \ldots, n; \quad r = 1, 2, \ldots, R. \tag{14}$$

The set $\boldsymbol{w} = \{w_1, w_2, \ldots, w_n\}$, calculated according to Eq. (14), is the objective importance of product attributes. However, the decision-maker may have their own preference. If the decision-maker provides their own weight set, denoted as $\boldsymbol{\Gamma} = \{\gamma_1, \gamma_2, \ldots, \gamma_n\}$, the final set of weights can be obtained by weighted averaging with the objective importance set. Let $\boldsymbol{q} = \{q_1, q_2, \ldots, q_n\}$ be the weighted average weights, which are calculated by:

$$q_j = \lambda w_j + (1 - \lambda)\gamma_j \tag{15}$$

where λ is the probability of the decision-maker accepting the objective weights, $\lambda \in [0, 1]$.

3.2. Sentiment analysis

In this subsection, three different machine learning methods, namely NB, LR, and SVM, are used to identify the sentiment orientations of online reviews. In addition, ER theory is used to integrate the predicted classification results of the three classifiers. The process of sentiment analysis based on online reviews in this study is shown in Fig. 5.

3.2.1. Converting preprocessed online reviews into feature vectors

Since machine learning algorithms cannot recognize the review texts directly, we use the bag-of-words (BOW) model to convert the texts into feature vectors. After preprocessing, we mainly retain nouns, adjectives, verbs, and adverbs. Then, the review D_r can be converted into a vector $F = (f_1, f_2, \ldots, f_H)$ consisting of H features, and the weights corresponding to the H features are denoted by $\mu_r = (\mu_{r1}, \mu_{r2}, \ldots, \mu_{rH})$, respectively. Through text vectorization, the preprocessed review texts can be converted into a high-dimensional feature vector matrix. The term frequency-inverse document frequency (TF-IDF) method can be used to calculate the feature weights in the vector matrix. TF indicates that the more frequently a word appears in a review, the more important the word is for that review. Conversely, IDF indicates that the more frequently a word appears in all reviews, the less important the word is. Combining the two aspects, the feature weights of the review texts can be calculated, and the greater the feature weight of the word, the greater the ability of the word to distinguish semantics. Therefore, the value of μ_{rh} can be calculated by:

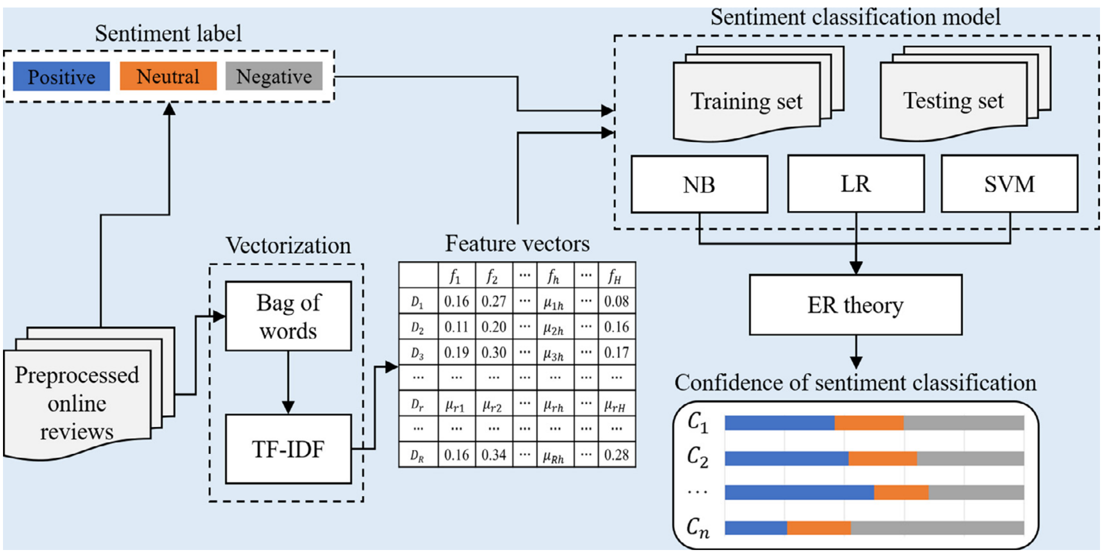


Fig. 5. The process of sentiment analysis.

$$\mu_{rh} = \frac{n_{rh}}{\sum_{h=1}^{m} n_{rh}} \times \log \frac{|\mathbb{D}|}{|\{r : f_h \in D_r\}| + 1}, \tag{16}$$

where n_{rh} represents the frequency of the feature f_h that appears in the review D_r, $|\mathbb{D}|$ denotes the total number of reviews, and $|\{r : f_h \in D_r\}|$ denotes the number of reviews containing the feature f_h $(h = 1, 2, \ldots, H)$. Taking three online reviews as an example, Table 6 shows the results of text vectorization after pre-processing, where D_1 = "*Appearance: very beautiful and good shape*", D_2 = "*The new computer is great*", and D_3 = "*Poor heat dissipation*".

3.2.2. Identifying the sentiment orientations of online reviews based on machine learning

a) **Naive Bayes**

NB algorithm is the most common algorithm for classification based on prior probability in Bayesian classification. Its theoretical premise is that the features are independent of each other, which is defined as:

$$P(O_i|F) = \frac{P(F|O_i)P(O_i)}{P(F)}, \tag{17}$$

where $F = \{f_1, f_2, \ldots, f_m\}$ represents a set of feature words, and O_i represents the i-th category in the classification $(i = 1, 2, \ldots, k)$. When there is $P(O_i|F) > P(O_j|F)$ $(j = 1, 2, \ldots, k, j \neq i)$, the unknown sample is judged as the O_i category.

b) **Logistic regression**

LR is a simple and efficient classification model in machine learning. Its main idea is to establish a regression formula for the classification boundary. The predicted value is obtained via linear regression. By mapping through the Sigmoid function, the dependent variable is transformed into the probability value in $[0, 1]$, and the regression formula is given as:

$$y = \sigma(\omega^T x + b) = \frac{1}{1 + e^{-(\omega^T x + b)}}, \tag{18}$$

where ω^T is the weight that has been trained. When putting the data x that needs to be predicted into Eq. (18), the corresponding probability value can be obtained.

c) **Support vector machine**

SVM is a classic classification algorithm in machine learning, and previous studies show that SVM is superior to other classifiers in terms of its classification effect [14]. Its basic theoretical idea is to find the hyperplane with the largest interval between the divided feature spaces through the training set. Using (x_i, y_i) to represent the sample points, the SVM model can be expressed as the following optimization problem:

$$\begin{aligned} &\min_{\omega,b} \tfrac{1}{2}\|\omega\|^2 \\ &\text{s.t. } y_i(\omega \cdot x_i + b) \geqslant 1, \quad i = 1, 2, \ldots, N, \end{aligned} \tag{19}$$

where b is the deviation vector that has also been trained. In addition, for nonlinear classification problems, the core idea is to transform the nonlinear problem into a high-dimensional space using kernel functions. Common kernel functions include the linear kernel, Gaussian kernel, and polynomial kernel. Through coding design, the SVM model in this paper uses the Gaussian kernel function and adopts the one VS rest (OVR) strategy to achieve sentiment multi-classification.

3.2.3. Evidence combination of three classifiers based on evidential reasoning

We need to evaluate the effect of machine learning according to the classification results. The confusion matrix of the classification effect is shown in Table 7. Here, P is used to denote positive reviews, M is used to denote neutral reviews, and N is used to denote negative reviews. PM indicates that the classifier classifies positive reviews as neutral reviews, and the meaning of the remaining symbols can be analogized. Additionally, $TOTAL$ is used to represent the number of all classified reviews.

Commonly used evaluation indicators are shown in Table 8 (taking the positive reviews as an example). We use ER theory to aggregate the results of the three classifiers and obtain the final sentiment classification results. The procedure is shown as follows:

Table 6
The feature vectors of online reviews.

	Appearance	Beautiful	Computer	Dissipation	Good	Great	Heat	New	Poor	Shape	Very
D_1	0.45	0.45	0	0	0.45	0	0	0	0	0.45	0.45
D_2	0	0	0.58	0	0	0.58	0	0.58	0	0	0
D_3	0	0	0	0.58	0	0	0.58	0	0.58	0	0

Table 7
Confusion matrix.

	Predicted positive	Predicted neutral	Predicted negative
True positive	*PP*	*PM*	*PN*
True neutral	*MP*	*MM*	*MN*
True negative	*NP*	*NM*	*NN*

Step 1. The different sentiment orientations of online reviews are regarded as a frame of discernment $\Theta = \{S_1, S_2, S_3\}$, where S_1, S_2, and S_3 represent negative, neutral, and positive sentiment orientations, respectively.

Step 2. The results of the classification are obtained by calculating the probability of different sentiment orientations, that is, the confidence in evidential reasoning. $\beta^q_{k,ij}$ is used to represent the confidence, which can be calculated by:

$$\beta^q_{k,ij} = \frac{num^q_{k,ij}}{\Sigma^3_{q=1} num^q_{k,ij}} \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n; \quad k = 1, 2, 3, \tag{20}$$

where $num^q_{k,ij}$ represents the number of times that the sentiment orientation of the product A_i for attribute C_j is assigned to the S_q level by the k-th classifier. Table 9 shows the confidence distribution matrix of the sentiment orientation of the product A_i for attribute C_j, where m_1, m_2, and m_3 represent the three classifiers of NB, LR, and SVM, respectively.

Step 3. We regard a classifier as a piece of evidence. To calculate the weight of the evidence, we normalize the accuracy of the classifier, which is expressed as:

$$w^e_k = \frac{accuracy_k}{\sum_{k=1}^{3} accuracy_k}, \tag{21}$$

where w^e_k denotes the k-th weight of the evidence and $accuracy_k$ denotes the k-th accuracy of the classifier. Then, we use Eqs. (4) and (5) to obtain the corresponding basic probability assignment.

Step 4. The final sentiment classification probability can be obtained by using the combination rules shown in Eqs. (9)–(12). β^q_{ij} is denoted as the confidence after combination that the sentiment orientation of the product A_i for attribute C_j is assigned to the S_q level.

3.3. Product ranking

In what follows, we rank products based on the results of sentiment analysis. Notably, products with more positive reviews are better than those with more negative reviews. Therefore, SD rules are used to determine the $\overline{\text{SD}}$ relations between pairwise products, following which the ranking results can be obtained by using the PROMETHEE method.

3.3.1. Identifying the stochastic dominance matrix of products based on SD rules

Consider two arbitrary products, A_i and A_k, in the MCDM problem. Let ζ_{ij} denote the evaluation level of product A_i for attribute C_j. According to the confidence of sentiment classification after the evidence combination calculated in Section 3.2.2, the probability distribution function $P(\zeta_{ij})$ can be represented by:

$$P(\zeta_{ij}) = \begin{cases} \beta^1_{ij}, & \zeta_{ij} = S_1 \\ \beta^2_{ij}, & \zeta_{ij} = S_2 \\ \beta^3_{ij}, & \zeta_{ij} = S_3 \end{cases} \quad \begin{matrix} i = 1, 2, \ldots, m \\ j = 1, 2, \ldots, n. \end{matrix} \tag{22}$$

Let the sentiment classification level be expressed as a numerical value, that is, $S = \{S_1 = -1, S_2 = 0, S_3 = 1\}$. Then, the mathematical expectation e_{ij} of evaluation level ζ_{ij} can be calculated by:

Table 8
Evaluation indicators of machine learning.

Indicators	Explanations	Equations
Accuracy	The proportion of samples correctly classified.	$accuracy = \frac{NN+MM+PP}{TOTAL}$
Precision	The proportion of samples predicted to be correctly classified in the category.	$precision = \frac{PP}{PP+MP+NP}$
Recall	The proportion of samples that are actually in this category and that are classified correctly.	$recall = \frac{PP}{PP+PM+PN}$
The F1-score	The harmonic average of precision and recall.	$F1\text{-}score = \frac{2 * precision * recall}{precision+recall}$

Table 9
Confidence distribution matrix.

	m_1	m_2	m_3
S_1	$\beta^1_{1,ij}$	$\beta^1_{2,ij}$	$\beta^1_{3,ij}$
S_2	$\beta^2_{1,ij}$	$\beta^2_{2,ij}$	$\beta^2_{3,ij}$
S_3	$\beta^3_{1,ij}$	$\beta^3_{2,ij}$	$\beta^3_{3,ij}$

$$e_{ij} = \sum_{q=1}^{3} \beta^q_{ij} S_q. \tag{23}$$

The cumulative distribution function of the evaluation level ζ_{ij} is as follows:

$$F_{ij}(x) = \sum_{\zeta_{ij} \leqslant x} P(\zeta_{ij}) = \begin{cases} 0, & x < S_1 \\ \beta^1_{ij}, & S_1 \leqslant x < S_2 \\ \beta^1_{ij} + \beta^2_{ij}, & S_2 \leqslant x < S_3 \\ 1, & S_3 \leqslant x. \end{cases} \tag{24}$$

Let $\overline{\mathrm{SD}}$ denote the SD relations between each pair of products, where $\overline{\mathrm{SD}} \in \{\mathrm{FSD}, \mathrm{SSD}, \mathrm{TSD}\}$. Then, we use the SD rules in Definitions 6–8 to compare the cumulative distribution functions between each pair of products and establish a $\mathrm{SD}_j = \left[\sigma^j_{ik}\right]_{m \times m}$ matrix for attribute C_j, where σ^j_{ik} represents the possible SD relation between the cumulative distribution function of the evaluation levels ζ_{ij} and ζ_{kj}. Therefore, σ^j_{ik} can be denoted as:

$$\sigma^j_{ik} = \begin{cases} \mathrm{FSD}, & F_{ij}\mathrm{FSD}F_{kj} \Longleftrightarrow A_i\mathrm{FSD}A_k \\ \mathrm{SSD}, & F_{ij}\mathrm{SSD}F_{kj} \Longleftrightarrow A_i\mathrm{SSD}A_k \\ \mathrm{TSD}, & F_{ij}\mathrm{SSD}F_{kj} \Longleftrightarrow A_i\mathrm{SSD}A_k \\ -, & \mathrm{no}\overline{\mathrm{SD}}\mathrm{relation}. \end{cases} \tag{25}$$

3.3.2. Determining a ranking order of products

Based on the SD relations between pairwise products, we use the PROMETHEE-II method to obtain the final product ranking results. The PROMETHEE method, which Brans et al. [41] proposed, is a well-known MCDM method based on outranking relations.

The decision matrix $D = [e_{ij}]_{m \times n}$ is first constructed, where e_{ij} represents the evaluation value of the product A_i for attribute C_j, that is, the mathematical expectation of the evaluation level ζ_{ij} in the above calculation process. This can be shown as:

$$D = \begin{bmatrix} e_{11} & e_{12} & \dots & e_{1n} \\ e_{21} & e_{22} & \dots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{m1} & e_{m2} & \dots & e_{mn} \end{bmatrix} \tag{26}$$

To facilitate the calculation, we choose the linear criterion of the segmented form in the PROMETHHE-II method to construct the preference function. Then, we calculate the degree of preference $P_j(A_i, A_k)$ of product A_i compared to product A_k for attribute C_j by:

$$P_j(A_i, A_k) = \begin{cases} 1, & F_{ij}\overline{\mathrm{SD}}F_{kj} \text{ and } d_j(A_i, A_k) \geqslant p_j \\ \frac{d_j(A_i, A_k)}{p_j}, & F_{ij}\overline{\mathrm{SD}}F_{kj} \text{ and } 0 < d_j(A_i, A_k) < p_j \\ 0, & \text{else}. \end{cases} \tag{27}$$

where $d_j(A_i, A_k) = e_{ij} - e_{kj}$, and p_j is the preference threshold for attribute C_j, which is set by the decision-maker.

For the above cases, the priority relation between A_i and A_k can be given as:

(1) If there is $F_{ij}\overline{\mathrm{SD}}F_{kj}andd_j(A_i, A_k) \geqslant p_j$, this means that A_i is strictly preferred to A_k concerning C_j;
(2) If there is $F_{ij}\overline{\mathrm{SD}}F_{kj}and0 < d_j(A_i, A_k) < p_j$, this means that A_i is weakly preferred to A_k concerning C_j;
(3) If there is no $\overline{\mathrm{SD}}$ between F_{ij} and F_{kj}, this means that there is indifference between A_i and A_k concerning C_j.

Considering all of the attributes, the overall priority degree $P(A_i, A_k)$ of product A_i compared to product A_k can be calculated by:

$$P(A_i, A_k) = \sum_{j=1}^{n} q_j P_j(A_i, A_k) \quad i \neq k. \tag{28}$$

To calculate the degree of superiority and inferiority of a product compared to the other products, the PROMETHEE-II method defines the positive flow and negative flow of the product as:

$$\phi^{+}(A_i) = \frac{1}{m-1} \sum_{i=1, i\neq k}^{m} P(A_i, A_k), \tag{29}$$

$$\phi^{-}(A_i) = \frac{1}{m-1} \sum_{i=1, i\neq k}^{m} P(A_k, A_i). \tag{30}$$

where $\phi^{+}(A_i)$ represents the positive flow, that is, the priority degree of A_i over the other products. $\phi^{-}(A_i)$ represents the negative flow, that is, the priority degree, of the other products over A_i.

Thus, the net flow is calculated using the following formula, and products are ranked according to their value. Notably, the higher the value of $\phi(A_i)$, the better product A_i is.

$$\phi(A_i) = \phi^{+}(A_i) - \phi^{-}(A_i). \tag{31}$$

The process of ranking products based on online reviews is now summarized in Algorithm 1 as follows.

Algorithm 1 The process of ranking products

Input: w_j: the objective weight of attribute C_j; γ_j: the subjective weight of attribute C_j; λ: the acceptance probability of the decision-maker; β_{ij}^{q}: the confidence of the sentiment orientation; p_j: the preference threshold for attribute C_j;
Output: the net flow $\phi(A_i)$;

compute the cumulative distribution function F_{ij};
for $j = 1 \rightarrow n$ **do**
  for $i, k = 1 \rightarrow m; i \neq k$ **do**
    if F_{ij} FSD F_{kj} **then**
      A_i FSDA_k concerning C_j;
    else if F_{ij} SSD F_{kj} **then**
      A_i SSDA_k concerning C_j;
    else if F_{ij} TSD F_{kj} **then**
      A_i TSD A_k concerning C_j;
    else
      no $\overline{\text{SD}}$ relation;
    end if
  end for
end for
$e_{ij} \leftarrow \sum_{q=1}^{3} \beta_{ij}^{q} S_q$;
compute the decision matrix $D = [e_{ij}]_{m\times n}$;
for $j = 1 \rightarrow n$ **do**
  $q_j \leftarrow \lambda w_j + (1-\lambda)\gamma_j$;
  for $i, k = 1 \rightarrow m; i \neq k$ **do**
    compute the degree of preference $P_j(A_i, A_k)$ concerning C_j;
    $P(A_i, A_k) \leftarrow \sum_{j=1}^{n} q_j P_j(A_i, A_k)$;
    compute the net flow $\Phi(A_i)$;
  end for
end for

4. Case study

This section presents a case study on ranking computer products from JD Mall based on our proposed method and conducts the theoretical analysis of ranking results to illustrate the feasibility and effectiveness of the proposed method.

4.1. Problem description

As one of China's largest comprehensive online retailers, JD Mall plays an important role in China's e-commerce. Today, computer products are essential office tools, and online reviews of such products are usually more objective. Therefore, this case study aims to rank the best-selling computer products from JD Mall. Fig. 6 shows a screenshot of a consumer's review on JD Mall after purchasing a computer product.

Consider a consumer who wants to buy a computer product and has the following six available products to choose from, namely A_1(Dell), A_2(HP), A_3(Lenovo ThinkBook), A_4(Lenovo Air), A_5(Honor), and A_6(MI). As mentioned in SubSection 3.1.1, the raw online reviews of the above six products are crawled from the JD Mall website (https://www.jd.com/) using Bazhuayu crawler software (https://www.bazhuayu.com/). Due to the limitations of the JD Mall website, a maximum of 1000 reviews of each sentiment orientation can be crawled, and Table 10 shows the number of raw reviews crawled.

4.2. Implementation

For the raw data, we first remove invalid reviews, especially those without review texts but with extreme star ratings. Since the consumers have not provided subjective evaluation attributes and weights, we first preprocess the obtained online reviews and use the TextRank algorithm to obtain the initial attribute set. Then, we construct a synonym table based on expert opinions to summarize the final product attributes, as shown in Table 11. In addition, Table 12 shows the number of times each attribute in the reviews appeared in different sentiment orientations, so the total counts here are different from the total number of reviews.

We use Eq. (14) to calculate the importance of attributes, which is $w = \{0.299, 0.189, 0.414, 0.098\}$. Suppose that the decision-maker validates and agrees with the objective importance of attributes, i.e., in this case, the acceptance probability $\lambda = 1$ and $q = w = \{0.299, 0.189, 0.414, 0.098\}$.

Before using machine learning for sentiment classification, the reviews need to be labeled. The labeling rules are as follows: Comments with 5-star ratings are labeled as positive reviews, represented by label "1"; products with 2-, 3-, or 4-star ratings are labeled as neutral reviews, represented by label "0"; products with 1-star ratings are labeled as negative reviews, represented by label "-1".

Then, we use NB, LR, and SVM as classifiers to identify the sentiment orientations of online reviews, with accuracies of 76.2%, 76.8%, and 78.3%, respectively. Fig. 7 shows the classification effects of the three classifiers for the evaluation indicators. Additionally, Table 13 shows the confidence distribution matrix of the sentiment orientations, which is constructed by using Eq. (20).

Then, based on Eq. (21), we use ER theory to combine the results of the three classifiers, as shown in Table 14.

By using Eqs. (22)–(24) to calculate the cumulative distribution function of the six products for each attribute, the function graphs are shown in Fig. 8 respectively..

According to Definitions 6–8, the SD relations between each pair of products for attribute C_j can be expressed as:

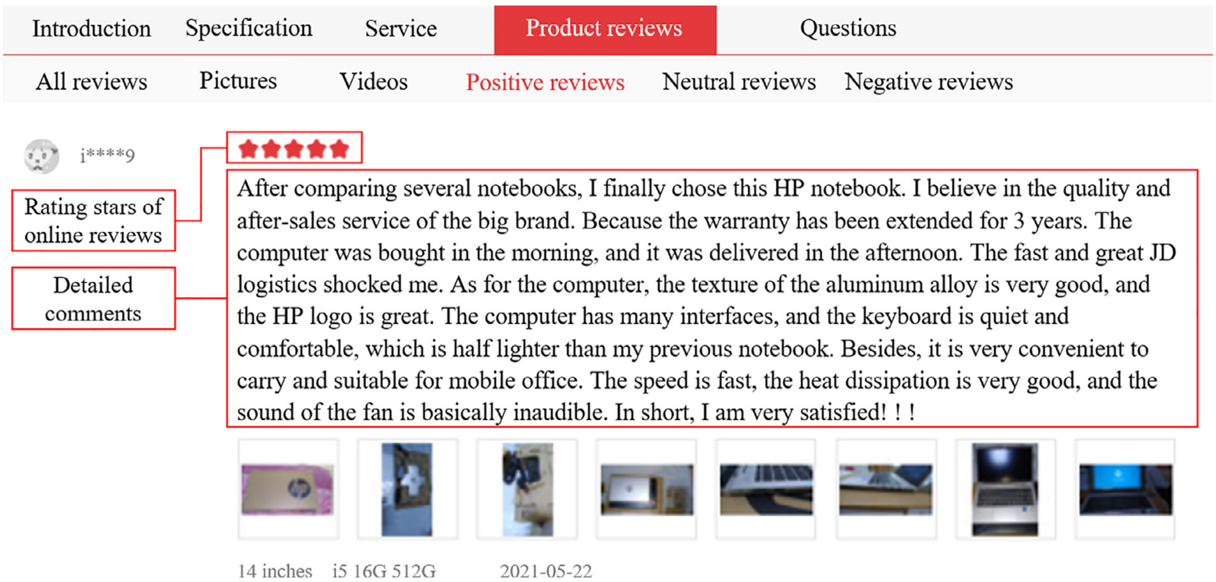


Fig. 6. Screenshot of a review posted on JD Mall.

Table 10
Reviews of products crawled from JD Mall.

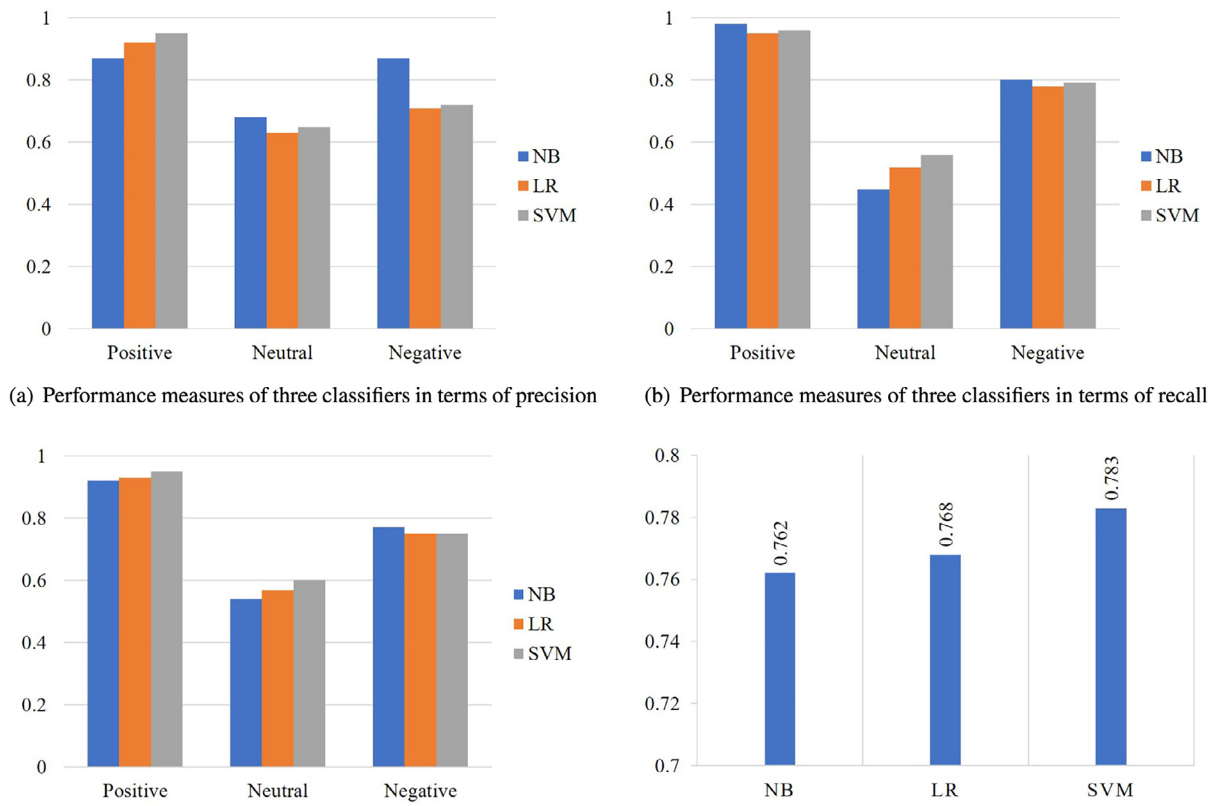
	A_1	A_2	A_3	A_4	A_5	A_6
1 star	880	1000	949	1000	1000	930
2 star	177	337	112	246	251	210
3 star	237	504	321	498	548	340
4 star	112	159	77	256	287	166
5 star	910	1000	1000	1000	910	910
Total numbers	2316	3000	2459	3000	2996	2556

Table 11
Product attributes and synonyms.

Notations	Attributes	Synonyms
C_1	Appearance	Screen, appearance, color, design, shape
C_2	Configuration	Keyboard, fan, mouse, camera, quality, material
C_3	Performance	Speed, effect, performance, boot, sound, software, system, black screen, cooling, video
C_4	Price-quality ratio	Price-quality ratio, price

Table 12
Overall evaluation of each attribute for sentiment orientation.

	C_1	C_2	C_3	C_1
Positive	4586	2194	4891	1296
Neutral	1508	1150	2490	460
Negative	886	1074	2272	539
Total counts	6980	4418	9653	2295



(a) Performance measures of three classifiers in terms of precision
(b) Performance measures of three classifiers in terms of recall
(c) Performance measures of three classifiers in terms of F1-scores
(d) Performance measures of three classifiers in terms of accuracy

Fig. 7. The results of the evaluation indicators for classifiers.

Table 13
The confidence of sentiment classification.

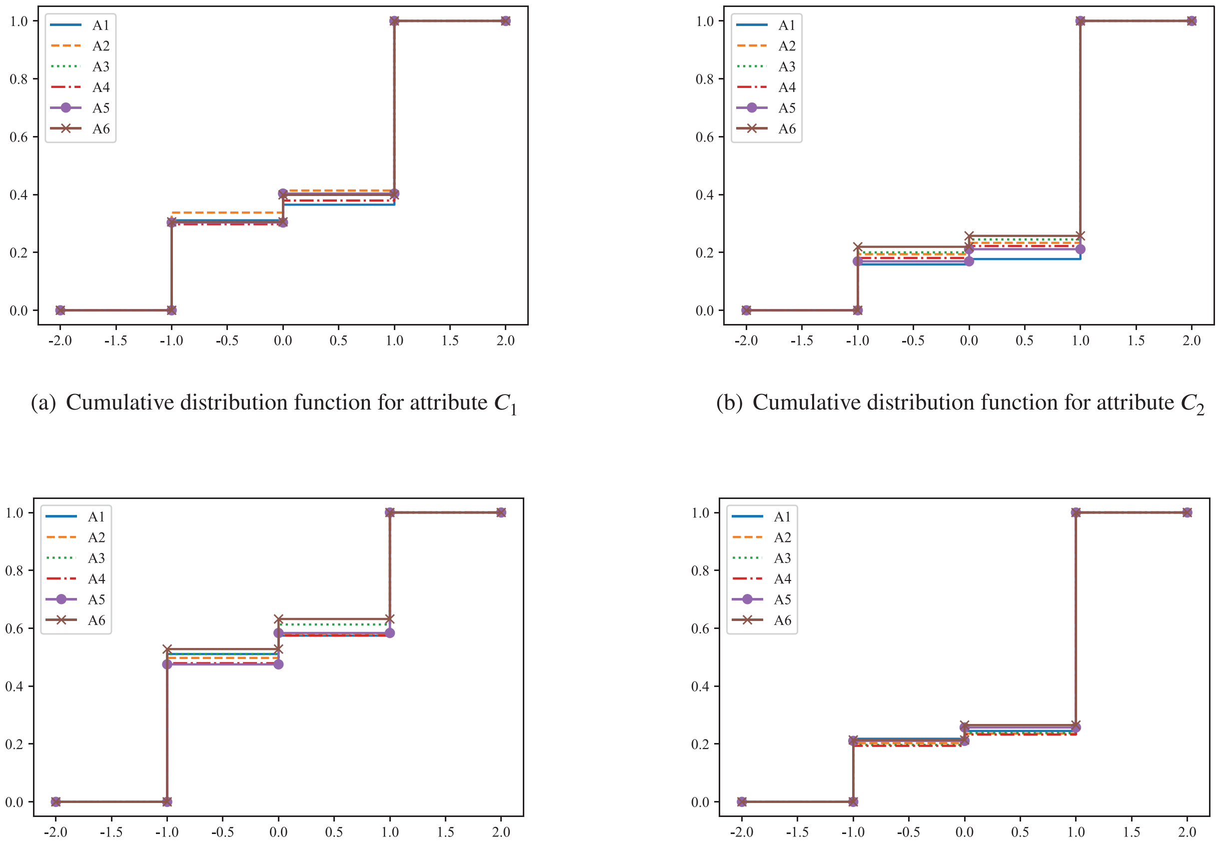
		C_1			C_2			C_3			C_4		
		NB	LR	SVM	NB	LR	SVM	NB	LR	SVM	NB	LR	SVM
A_1	−1	0.294	0.351	0.353	0.181	0.204	0.203	0.453	0.518	0.519	0.112	0.133	0.519
	0	0.105	0.048	0.046	0.040	0.017	0.018	0.120	0.055	0.054	0.035	0.014	0.054
	1	0.601	0.601	0.601	0.779	0.779	0.779	0.427	0.427	0.427	0.853	0.853	0.427
A_2	−1	0.312	0.378	0.367	0.206	0.243	0.236	0.442	0.508	0.499	0.099	0.119	0.499
	0	0.131	0.066	0.076	0.073	0.036	0.043	0.138	0.072	0.081	0.033	0.012	0.081
	1	0.557	0.557	0.557	0.721	0.721	0.721	0.420	0.420	0.420	0.868	0.868	0.420
A_3	−1	0.276	0.354	0.341	0.208	0.251	0.243	0.441	0.523	0.511	0.084	0.103	0.511
	0	0.157	0.079	0.092	0.083	0.041	0.048	0.168	0.087	0.099	0.038	0.018	0.099
	1	0.567	0.567	0.567	0.709	0.709	0.709	0.390	0.390	0.390	0.878	0.878	0.390
A_4	−1	0.281	0.340	0.331	0.194	0.228	0.223	0.425	0.491	0.483	0.095	0.110	0.483
	0	0.134	0.075	0.084	0.075	0.041	0.046	0.153	0.086	0.094	0.034	0.019	0.094
	1	0.585	0.585	0.585	0.731	0.731	0.731	0.422	0.422	0.422	0.871	0.871	0.422
A_5	−1	0.282	0.345	0.333	0.184	0.218	0.210	0.419	0.487	0.479	0.116	0.138	0.479
	0	0.155	0.092	0.104	0.074	0.041	0.048	0.167	0.099	0.107	0.044	0.022	0.107
	1	0.563	0.563	0.563	0.742	0.742	0.742	0.414	0.414	0.414	0.840	0.840	0.414
A_6	−1	0.283	0.348	0.337	0.231	0.265	0.263	0.459	0.534	0.523	0.097	0.121	0.523
	0	0.150	0.085	0.095	0.070	0.036	0.039	0.167	0.092	0.102	0.056	0.032	0.102
	1	0.567	0.567	0.567	0.698	0.698	0.698	0.374	0.374	0.374	0.847	0.847	0.374

Table 14
Sentiment confidence distribution based on the combination of ER theory.

C_1	S_1	S_2	S_3	C_2	S_1	S_2	S_3
A_1	0.311	0.054	0.635	A_1	0.159	0.018	0.823
A_2	0.338	0.076	0.586	A_2	0.194	0.039	0.767
A_3	0.306	0.093	0.601	A_3	0.200	0.045	0.755
A_4	0.297	0.082	0.621	A_4	0.181	0.041	0.778
A_5	0.303	0.100	0.597	A_5	0.169	0.042	0.789
A_6	0.306	0.093	0.601	A_6	0.219	0.038	0.743
C_3	S_1	S_2	S_3	C_4	S_1	S_2	S_3
A_1	0.511	0.064	0.426	A_1	0.218	0.027	0.755
A_2	0.497	0.083	0.420	A_2	0.203	0.033	0.764
A_3	0.511	0.102	0.387	A_3	0.197	0.041	0.762
A_4	0.479	0.096	0.425	A_4	0.194	0.039	0.767
A_5	0.475	0.108	0.416	A_5	0.211	0.046	0.743
A_6	0.528	0.104	0.368	A_6	0.214	0.051	0.735

$$SD_1 = \begin{bmatrix} - & & FSD & & & \\ & - & & & & \\ & FSD & - & & & FSD \\ TSD & FSD & FSD & - & FSD & FSD \\ & FSD & & & - & \\ & FSD & FSD & & & - \end{bmatrix}$$

$$SD_2 = \begin{bmatrix} - & FSD & FSD & FSD & FSD & FSD \\ & - & FSD & & & FSD \\ & & - & & & FSD \\ & FSD & FSD & - & & FSD \\ & FSD & FSD & FSD & - & FSD \\ & & & & & - \end{bmatrix}$$



(a) Cumulative distribution function for attribute C_1

(b) Cumulative distribution function for attribute C_2

(c) Cumulative distribution function for attribute C_3

(d) Cumulative distribution function for attribute C_4

Fig. 8. Cumulative distribution function graphs.

$$SD_3 = \begin{bmatrix} - & & FSD & & & FSD \\ SSD & - & FSD & & & FSD \\ & & - & & & FSD \\ FSD & FSD & FSD & - & & FSD \\ SSD & SSD & FSD & & - & FSD \\ & & & & & - \end{bmatrix}$$

$$SD_4 = \begin{bmatrix} - & & & & & \\ FSD & - & & & FSD & FSD \\ FSD & SSD & - & & FSD & FSD \\ FSD & FSD & FSD & - & FSD & FSD \\ & & & & - & FSD \\ & & & & & - \end{bmatrix}$$

Based on Table 14, a decision matrix $D = [e_{ij}]_{6\times4}$ can be constructed by using Eqs. (23) and (26).

$$D = \begin{bmatrix} 0.324 & 0.664 & -0.085 & 0.537 \\ 0.248 & 0.573 & -0.077 & 0.561 \\ 0.294 & 0.555 & -0.124 & 0.565 \\ 0.323 & 0.597 & -0.054 & 0.574 \\ 0.293 & 0.620 & -0.059 & 0.532 \\ 0.296 & 0.523 & -0.160 & 0.521 \end{bmatrix}.$$

Based on Eqs. 27,28, we set the preference threshold $p_j = 0.03$ $(j = 1,2,3,4)$, then the overall priority matrix $P = [P(A_i, A_k)]_{6\times6}$ can be obtained and shown as follows:

$$P = \begin{bmatrix} 0 & 0.430 & 0.460 & 0.190 & 0.190 & 0.460 \\ 0.312 & 0 & 0.384 & 0 & 0.290 & 0.760 \\ 0.280 & 0.280 & 0 & 0 & 0.300 & 0.760 \\ 0.570 & 0.729 & 0.782 & 0 & 0.540 & 0.976 \\ 0.234 & 0.592 & 0.460 & 0.146 & 0 & 0.570 \\ 0 & 0.240 & 0.016 & 0 & 0 & 0 \end{bmatrix}$$

Thus, we can calculate the positive flow $\phi^+(A_i)$, the negative flow $\phi^-(A_i)$, and the net flow $\phi(A_i)$ according to Eqs. (29)–(31); the results are given in Table 15. Notably, the final product ranking order is $A_4 \succ A_5 \succ A_1 \succ A_3 \succ A_2 \succ A_6$.

4.3. Sensitivity analysis

In this subsection, we conduct sensitivity analysis. Note that the decision-maker sets the preference threshold $p_j = 0.03$ $(j = 1,2,3,4)$, and the change in p_j impacts the calculation results. Corrente et al. [42] propose an SMAA-PROMETHEE method for studying the different ranking results when varying the parameters in the model. However, their model fails to consider the situation in which the preference thresholds are also changed. Therefore, we propose a novel SMAA-PROMETHEE method for the sensitivity analysis of the preference threshold p_j. Furthermore, as mentioned in Section 3, we consider the probability of accepting objective weights when the decision-maker has their own weighting preferences.

Let the value function $\phi(A_i) = \phi(i,p,q,\lambda)$ represent the whole process of the PROMETHEE method. The function $\phi(i,p,q)$ is used to measure the change in net flow by changing the threshold vector p, the acceptance probability λ, and the integrated weight vector q. Denote that the preference information of threshold p has a probability density function $f_P(p)$ on the feasible threshold space P. Similarly, the preference information of the acceptance probability λ and weight q have probability density functions $f_\Lambda(\lambda), f_Q(q)$ on the feasible spaces Λ and Q, respectively.

$$P = \{p \in R : p_j > 0\}, \tag{32}$$

$$Q = \left\{ q \in R : q_j > 0, \sum_{j=1}^{n} q_j = 1 \right\}, \tag{33}$$

$$\Lambda = \{\lambda \in R : 0 \leqslant \lambda \leqslant 1\}. \tag{34}$$

Thus, we denote that the joint probability density function $f_U(u)$ is uniformly distributed on the feasible parameter space U.

$$U = P \times Q \times \Lambda = \{u = [p,q,\lambda] : p \in P, w \in W, \lambda \in \Lambda\}, \tag{35}$$

$$f_U(u) = \begin{cases} \frac{1}{\mathrm{vol}(U)}, & u \in U \\ 0, & \text{otherwise}. \end{cases} \tag{36}$$

Based on the SMAA method, the ranking order of alternative products is calculated by:

$$\mathrm{rank}(i,p,q,\lambda) = 1 + \sum_{k \neq i} \rho[\phi(k,p,q,\lambda) > \phi(i,p,q,\lambda)], \tag{37}$$

where $\rho(true) = 1, \rho(false) = 0$. $\mathrm{rank}(i,p,q,\lambda) = 1$ indicates that when the threshold vector is p and the weight vector is q, product A_i ranks the best; contrarily, $\mathrm{rank}(i,p,q,\lambda) = 6$ indicates that product A_i ranks the worst.

We define the favorable ranking factor U_i^r, which represents the set of preference information of p, λ, and q and satisfies product A_i ranking r.

$$U_i^r = \{p \in P, w \in W, \lambda \in \Lambda : \mathrm{rank}(i,p,q,\lambda) = r\}. \tag{38}$$

Consider the following five descriptive metrics with their definitions:

Table 15
The flow of each product.

	A_1	A_2	A_3	A_4	A_5	A_6
ϕ^+	0.346	0.349	0.324	0.719	0.400	0.051
ϕ^-	0.279	0.454	0.420	0.067	0.264	0.705
ϕ	0.067	−0.105	−0.096	0.652	0.136	−0.654

a) **Rank acceptability index (RAI)**

The RAI b_i^r denotes the share of all preference information that makes product A_i rank r.

$$b_i^r = \int_{u \in U_i^r} f_U(u)du = \iiint_{u \in U_i^r} f_P(p)f_Q(q)f_Q(q)dpdwd\lambda. \tag{39}$$

It can be seen that the value range of b_i^r is $[0, 1]$. The higher the value b_i^r, the greater the probability that product A_i will rank r, with u taking any value on U.

b) **Central threshold vector (CTV)**

The CTV is defined as the favorable first-rank thresholds of product A_i. It represents the most favorable threshold vector p for product A_i, which is calculated by:

$$p_i^c = \frac{1}{b_i^1} \iiint_{u \in U_i^r} pf_P(p)f_Q(q)f_\Lambda(\lambda)dpdwd\lambda. \tag{40}$$

Notably, p_i^c can only be calculated when b_i^1 of product A_i is non-zero.

c) **Central weight vector (CWV)**

The CWV is defined as the favorable first-rank weights of product A_i. It represents the most favorable weight vector q for product A_i, which is calculated by:

$$q_i^c = \frac{1}{b_i^1} \iiint_{u \in U_i^r} qf_P(p)f_Q(q)f_\Lambda(\lambda)dpdqd\lambda. \tag{41}$$

Similar to the definition of CTV p_i^c, CWV exists only when b_i^1 of product A_i is non-zero.

d) **Central probability factor (CPF)**

The CPF is defined as the favorable first-rank acceptance probability of product A_i. It represents the most favorable acceptance probability q for product A_i, which is calculated by:

$$\lambda^c = \frac{1}{b_i^1} \iiint_{u \in U_i^r} \lambda f_P(p)f_Q(q)f_\Lambda(\lambda)dpdqd\lambda. \tag{42}$$

CPF also exists only when b_i^1 of product A_i is non-zero.

e) **Pairwise winning indices (PWIs)**

The PWIs are defined as the probability that product A_i will be more preferred than product A_k.

$$p_{ik} = \iiint_{u \in U:\mathrm{rank}(i,p,q,\lambda) < \mathrm{rank}(k,p,w,\lambda)} f_P(p)f_Q(q)f_\Lambda(\lambda)dpdwd\lambda. \tag{43}$$

We use the Monte Carlo algorithm to simulate the above descriptive metrics, and the whole procedure is divided into the following steps:

(1) Determine the space of preference threshold $P = \{p_j \in R \mid 0.01 < p_j < 0.05, j = 1, 2, 3, 4\}$.
(2) Set the maximum number of simulations, $N = 10,000$. For the n-th simulation, select the random sets of threshold vector p^n, the acceptance probability λ from U, and the corresponding weight vector q^n. The integrated weight vector q^n) is obtained by randomly initializing the subjective weight vector of the decision-maker in Eq. (15). Then, calculate $\phi(i, p^n, q^n, \lambda^n)$ for each product A_i and obtain the ranking order of alternative products by using Eq. (37).
(3) If $n < N$, continue to execute (2); if $n = N$, then stop the simulation process and calculate the RAI, CTV, CWV, CPF, and PWIs for each product A_i $(i = 1, 2, \ldots, 6)$, respectively, by using the following formulas:

- RAI: $b_i^r \approx B_i^r/N$, where $B_i^r = \sum_{n \in N} \rho_1^n[\mathrm{rank}(i, p^n, q^n, \lambda^n) = r]$, $\rho_1^n(true) = 1$, and $\rho_1^n(false) = 0$;
- CTV: $p_i^c \approx \sum_{n \in N} \rho_2^n[\mathrm{rank}(i, p^n, q^n, \lambda^n) = 1]/B_i^1$, where $\rho_2^n(true) = p^n$ and $\rho_2^n(false) = 0$;
- CWV: $q_i^c \approx \sum_{n \in N} \rho_3^n[\mathrm{rank}(i, p^n, q^n, \lambda^n) = 1]/B_i^1$, where $\rho_3^n(true) = q^n$ and $\rho_3^n(false) = 0$;
- CPF: $\lambda^c \approx \sum_{n \in N} \rho_4^n[\mathrm{rank}(i, p^n, q^n, \lambda^n) = 1]/B_i^1$, where $\rho_4^n(true) = \lambda^n$ and $\rho_4^n(false) = 0$;
- PWIs: $p_{ik} \approx \sum_{n \in N}\left(\rho_1^n(\mathrm{rank}(i, p^n, w^n, \lambda^n) < \mathrm{rank}(k, p^n, w^n, \lambda^n))\right)/N$.

Based on the above steps, Tables 16–20 show the calculation results of the RAIs, CTVs, CWVs, CPFs, and PWIs after 10,000 Monte Carlo simulations. To intuitively display the RAIs, we visualize the data presented in Table 16 as Fig. 9.

It can be seen from Table 16 and Fig. 9 that products A_1, A_4, and A_5 all have the probability to be ranked first. However, product A_4 is the most likely to be ranked first since it has a higher RAI value ($b_4^1 = 0.9963$). Similarly, whether by comparing

Table 16
RAIs of alternative products.

	b_i^1	b_i^2	b_i^3	b_i^4	b_i^5	b_i^6
A_1	0.0003	0.0695	**0.9217**	0.0073	0.0012	0
A_2	0	0	0.0082	**0.9674**	0.0244	0
A_3	0	0	0.0003	0.0253	**0.9744**	0
A_4	**0.9963**	0.0028	0.0009	0	0	0
A_5	0.0034	**0.9277**	0.0689	0	0	0
A_6	0	0	0	0	0	**1**

Table 17
CTVs of alternative products.

		p_1	p_2	p_3	p_4
A_1	p_1^c	0.0350	0.0213	0.0292	0.0284
A_2	p_2^c	NE	NE	NE	NE
A_3	p_3^c	NE	NE	NE	NE
A_4	p_4^c	0.0295	0.0298	0.0296	0.0298
A_5	p_5^c	0.0271	0.0292	0.0345	0.0302
A_6	p_6^c	NE	NE	NE	NE

NE denotes that "The value does not exist".

Table 18
CWVs of alternative products.

		q_1	q_2	q_3	q_4
A_1	q_1^c	0.038	0.548	0.285	0.130
A_2	q_2^c	NE	NE	NE	NE
A_3	q_3^c	NE	NE	NE	NE
A_4	q_4^c	0.215	0.245	0.391	0.150
A_5	q_5^c	0.063	0.460	0.441	0.035
A_6	q_6^c	NE	NE	NE	NE

NE denotes that "The value does not exist".

Table 19
CPFs of alternative products.

	A_1	A_2	A_3	A_4	A_5	A_6
λ^c	0.0733	NE	NE	0.5027	0.0824	NE

NE denotes that "The value does not exist".

Table 20
The matrix of PWIs.

	A_1	A_2	A_3	A_4	A_5	A_6
A_1	0	0.9915	0.9988	0.0010	0.0691	1
A_2	0.0085	0	0.9753	0	0	1
A_3	0.0012	0.0247	0	0	0	1
A_4	0.9990	1	1	0	0.9964	1
A_5	0.9309	1	1	0.0036	0	1
A_6	0	0	0	0	0	0

RAIs or PWIs, we can determine that product A_5 has a greater probability of ranking second ($b_5^2 = 0.9277$), and product A_1 is best placed third ($b_1^3 = 0.9217$). Analogously, we can get the complete ranking order of the alternative products, that is, $A_4 \succ A_5 \succ A_1 \succ A_2 \succ A_3 \succ A_6$.

Notably, the ranking order after the SMAA simulation is different from the order calculated by setting the initial preference thresholds and weights. In the SMAA-PROMETHEE method, we calculate the ranking results when the thresholds, probability, and weights are randomly selected. From Table 17 and Table 18, it can be seen that when product A_4 is ranked first,

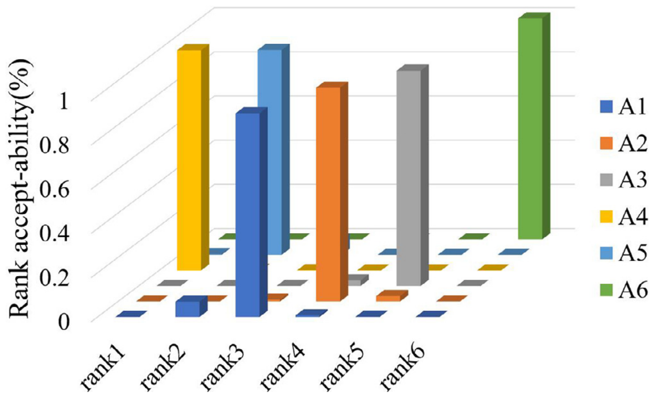


Fig. 9. RAIs plot of alternative products.

both the CTV (p_4^c) and CWV (w_4^c) are different from the initial settings, proving that different thresholds and weights influence the ranking results.

Furthermore, since A_2, A_3, and A_6 have no probability to be ranked first in the SMAA simulation, their CPFs do not exist according to Table 19. This indicates that whether or not the decision-maker accepts the objective weights, these products are unlikely to rank first. Conversely, if a product has a larger CPF, the decision-maker can have more subjective preferences when that product ranks first.

Therefore, based on the above analysis, the first ranking order, $A_4 \succ A_5 \succ A_1 \succ A_3 \succ A_2 \succ A_6$, is more suitable when the decision-maker is convinced of the initial preference thresholds and objective weights; however, the second-ranking order, $A_4 \succ A_5 \succ A_1 \succ A_2 \succ A_3 \succ A_6$, is recommended for the decision-maker who lacks professional knowledge, as it is more stable.

4.4. Comparative analysis

To illustrate the effectiveness of the method proposed in this study, we compare it with the method proposed by Jiang et al. [19]. The method in [19] is similar to the one that our ranking process involves, but it is interpreted and calculated from different perspectives, showing that the two methods have some similarities and differences. Fig. 10 shows the mechanism of the two methods in the ranking process. The decision steps in [19] are as follows:

According to the overall priority degree $P(A_i, A_k)$ of product A_i compared to product A_k in Eq. (28), an overall priority degree matrix $P = [P(A_i, A_k)]_{m\times m}$ of the pairwise comparisons of products can be established. Then, two vectors $X^+ = (\sigma_1^+, \sigma_2^+, \ldots, \sigma_m^+)$ and $X^- = (\sigma_1^-, \sigma_2^-, \ldots, \sigma_m^-)$, can be constructed, where $\sigma_i^+ = \max\{P(A_k, A_i) | k = 1, 2, \ldots, m; i \neq k\}$ and $\sigma_i^- = \max\{P(A_i, A_k) | k = 1, 2, \ldots, m; i \neq k\}$ $(i = 1, 2, \ldots, m)$.

Based on the vectors X^+ and X^-, two deviation degrees S_i^+ and S_i^- can be respectively calculated by:

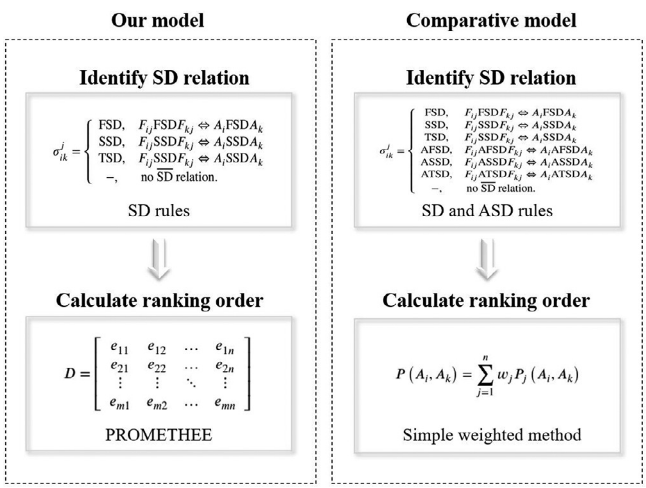


Fig. 10. Comparative results of the ranking order.

$$S_i^+ = \sum_{k=1,i\neq k}^{m} \left|\sigma_{ik} - \sigma_k^+\right| = \sum_{k=1,i\neq k}^{m} \sigma_k^+ - \sum_{k=1,i\neq k}^{m} \sigma_{ik}, \tag{44}$$

$$S_i^- = \sum_{k=1,i\neq k}^{m} \left|\sigma_{ki} - \sigma_k^+\right| = \sum_{k=1,i\neq k}^{m} \sigma_k^+ - \sum_{k=1,i\neq k}^{m} \sigma_{ki}. \tag{45}$$

Thus, the closeness coefficient I_i of product A_i can be calculated by:

$$I_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad i = 1, 2, \ldots, m. \tag{46}$$

The calculation results of the case study in this paper obtained using the method in [19] are shown in Table 21. Additionally, the comparative results obtained in Section 4.2, Section 4.3, and [19] are presented in Fig. 11. It can be seen that the final ranking order is $A_4 \succ A_1 \succ A_5 \succ A_2 \succ A_3 \succ A_6$. This ranking order is mostly the same as the order calculated in this paper, especially in terms of the best product (A_4) and worst product (A_6), which fully illustrates the validity of the method proposed in this paper.

In addition, we analyze the advantages of the method proposed in this paper in comparison to the comparative method, which is summarized as follows:

- The main advantage of the method in [19] is to use ASD as an important supplement of SD rules to make up for the lack of dominance relations between pairwise products. However, this advantage is not significant in identifying the dominance relation between products.
- The process in [19] uses a simple weighted method to rank products, which only considers very few decision factors compared to the method that combines SD and PROMETHEE. Thus, the results lack plausibility.
- Our study analyzes the sensitivity of the preference thresholds and weights to obtain more stable results for satisfying different preferences. Therefore, compared with the method in [19], the results derived from our model are more accurate.

4.5. Further discussion

Based on the above discussion, we provide a complete framework for ranking products based on online reviews. To illustrate the robustness and validity of the method proposed in this study, we conduct sensitivity analysis and comparative analysis, respectively. In general, the proposed method is open to further discussion, and we provide corresponding solution ideas from a business intelligence perspective:

- When solving the problem of product ranking based on online reviews, we usually crawl the consumers' reviews from the website. However, the reviews can be available online for a long period. That is, some reviews are posted earlier, while others are posted later, so their utility values for product ranking could differ. Moreover, the helpfulness of reviews can be measured using different utility values according to the posted time.
- Currently, the sentiment orientations of online reviews displayed on platforms are usually characterized by a positively skewed, bimodal (or J-shaped) distribution, which may influence the results of the sentiment analysis of online reviews. This phenomenon is also reflected in the case analyses of many existing studies [4,5]. We use machine learning to conduct a sentiment analysis of online reviews after labelling the reviews. For unbalanced data, the class weights can be set for the classifier parameters: assign higher weights to negative reviews and lower weights to positive reviews. This will make the classification more accurate.
- In addition, the PROMETHEE method is used to calculate the dominance degree between each pair of products and obtain reasonable ranking results. The decision-maker sets preference thresholds, so these rely on the expertise of the decision-maker. The effect of preference thresholds on ranking results is discussed in the sensitivity analysis, in which the space of preference thresholds is set at $(0.01, 0.05)$. The setting of preference thresholds will vary for different cases, and the most appropriate space for preference thresholds is a subject in need of further research.

4.6. Managerial implications

From the perspective of business intelligence, this study has several managerial implications:

Table 21
The calculation results based on [19].

	A_1	A_2	A_3	A_4	A_5	A_6
S_i^+	0.377	1.585	1.773	0.038	0.921	2.588
S_i^-	2.256	0.995	0.667	3.038	2.403	0.097
I_i	0.857	0.386	0.273	0.988	0.723	0.036

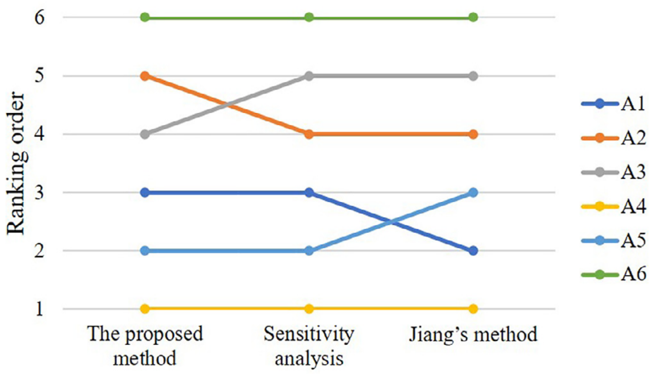


Fig. 11. Comparative results of the ranking order.

For the decision-maker, our proposed method can help them to select the most preferred and suitable product. From the objective attributes and weights we obtained, most consumers are more interested in the attribute "performance" of a computer and less focused on the attribute "price-quality ratio". In addition, the decision-maker can give subjective weights to the attributes of computer products, which are also considered in the product ranking process.

Based on this, suppliers can improve the quality of their products in response to consumer concerns. For example, according to Table 11, suppliers can boost the boot speed, optimize the system, etc. of computers. In accordance with Table 14, suppliers can mine valuable information from online reviews to obtain consumers' sentiment attitudes toward different attributes of the products, providing a basis for improving product quality. Furthermore, the method proposed in this paper allows suppliers to calculate the dominance degree of their products in comparison to those of other suppliers in terms of different attributes and improve on their shortcomings.

From the perspective of the platforms' marketing strategies and recommendation systems, at present, e-commerce platforms have a variety of ways to display products in order, such as per sales volume, price level, or the number of reviews. However, with the development of big data technologies and the increasing amount of interactive information available on platforms, consumers may become confused by the information displayed on the platform. In the short period during which consumers make their purchase decisions, the review information of products will not change significantly, so the platform should put product A_4 in a more prominent position to help consumers make their decisions. The framework proposed in this paper can also provide more comprehensive product ranking results through an end-to-end approach and aid in converting unstructured review information into ranking information that is more acceptable for users.

Furthermore, the integrated method proposed in this study can be applied to other decision-making problems with text-type data, such as the model of service satisfaction and the evaluation of production projects, among others.

5. Conclusions, limitations, and future studies

This paper discusses the problem of product ranking based on online reviews. By summarizing the limitations of the existing studies, an integrated method for product ranking through online reviews based on ER theory and SD rules is proposed. A data-driven decision analysis method is used to develop the model, which provides strong theoretical support for consumers in their choice of products based on online reviews. The main contributions of this paper are summarized as follows:

- We propose a novel method to analyze attribute extraction and weight calculation, which are not limited to those subjectively provided by decision-makers. Instead, our model uses reviews to objectively extract attributes and calculate weights. The corresponding results are also more suitable for the requirements of decision-makers.
- For sentiment analysis, this paper proposes a method based on machine learning and ER theory for identifying the sentiment orientations of online reviews. ER theory is considered an effective method for reducing uncertainty while fusing information. We propose a mechanism to aggregate the classification results obtained from machine learning by using ER theory, which provides a new perspective for sentiment analysis.
- We combine SD rules with the PROMETHEE method to obtain final ranking results and propose a new SMAA-PROMETHEE method for the sensitivity analysis of parameters, which can aid in obtaining more reasonable ranking results.

Although this study further analyzes the problem of product ranking through online reviews based on existing MCDM methods and provides a complete research framework, it still has some limitations.

- In an information-overloaded decision-making environment, there are many advertisements and false information in the crawled reviews. Since these reviews often have specific sentiment orientations, they may impact the reliability of the decision results.
- In terms of sentiment analysis, this study divides sentiment orientations into three categories. However, the categories can also be subdivided according to the different degrees of the sentiments, which provide more managerial implications for decision-making.

Thus, there are still some interesting issues worth pursuing in further studies. Nevertheless, we aim to improve our method for the sentiment analysis of online reviews. Based on the challenges and trends of sentiment analysis that Birjali et al. [43] highlight, we consider integrating different methods for sentiment analysis, such as natural language processing [44], a sentiment lexicon [45], reinforcement learning [46], and deep learning [47]. In addition, the studies on online reviews need not only focus on product ranking but could also focus on the improvement of products or services and subsequent feedback, which can help consumers make reasonable purchasing decisions. Further, for attribute extraction, we can also extend the studies to new product development [48]. These open problems will be considered in a future study.

CRediT authorship contribution statement

Jindong Qin: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition, Supervision. **Mingzhi Zeng:** Conceptualization, Methodology, Data curation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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