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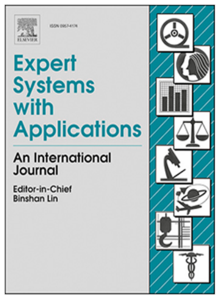

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Ranking products through online reviews considering the mass assignment of features based on BERT and *q*-rung orthopair fuzzy set theory

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Abstract

A product ranking method is an effective tool that can analyze a significant number of online product reviews to recommend suitable products to consumers. However, existing product ranking methods have two main limitations: (1) the high manual annotation costs and (2) the inability to express consumers' purchasing decisions because the information is limited to a single feature of each product. To overcome the limitations, this paper proposes a novel product ranking method considering the mass assignment of features based on bidirectional encoder representations using transformers (BERT) and q-rung orthopair fuzzy set theory. First, BERT is adopted to identify sentiment orientations of online product reviews and product features from online product reviews. Subsequently, the product features are clustered into groups and the relative frequencies of product features are obtained. Second, the relative frequencies of product features are transformed into q-rung orthopair fuzzy numbers based on mass assignment theory. Third, the q-rung orthopair fuzzy numbers are aggregated by the q-rung orthopair fuzzy generalized weighted Heronian mean operator to rank the products. Finally, we implement the method using a case study of six different phones to verify its feasibility. Using the case study, we also perform comparisons and sensitivity analyses, which demonstrate the superiority of our method.

Keywords: Online product reviews, BERT, q-rung orthopair fuzzy set, mass assignment, generalized weighted Heronian mean operator

1. Introduction

Product ranking methods support the consumers' purchase decisions (Zhang et al., 2016). Moreover, product ranking methods help improve customers' satisfaction when customers face a large volume of online product reviews. Indeed, with the emergence of large numbers of online product reviews on e-commerce platforms, online product reviews have become an important source of information for consumers to facilitate their purchase decisions. Due to time and energy constraints, most consumers are unable to inspect all available online product reviews. Therefore, research on product ranking methods based on online product reviews has attracted increasing attention in recent years (Bi et al., 2019; Fu et al., 2020; Fan et al., 2020; Liu et al., 2017b; Yang et al., 2019, 2020; Zeng et al., 2021).

Most existing studies on product ranking methods have used a third-step procedure. First, product features are extracted using data-mining techniques, such as part-of-speech tagging (Peng et al., 2014; Yang et al., 2019) and BiLSTM-CRF (Fu et al., 2020). Second, the sentiment orientations of product features are identified through sentiment analysis methods, such as part-of-speech tagging and pre-established sentiment dictionary (Fu et al., 2020). Furthermore, the frequency of each product feature is obtained (Fu et al., 2020; Peng et al., 2014; Yang et al., 2019). Subsequently, based on the frequency of each product feature, the information of each product feature is represented through different fuzzy sets, such as interval type-2 fuzzy sets (Bi et al., 2019), hesitant fuzzy sets (Zhang et al., 2020b), intuitionistic fuzzy sets (IFSs) (Çalı & Balaman, 2019; Liu et al., 2017b),interval-valued intuitionistic fuzzy sets (Liu et al., 2017a), interval-valued Pythagorean fuzzy sets (Fu et al., 2020), and q-rung orthopair fuzzy sets (q-ROFSs) (Yang et al., 2020). Third, the information from each product feature is used to rank products using various kinds of ranking approaches, such as TOPSIS (Liu et al., 2017a), VIKOR (Ren et al., 2017), PROMETHEE (Peng et al., 2014), and aggregation operator (Fu et al., 2020). However, previous research on product ranking commonly requires the sentiment orientations of each feature, which increase the difficulty of acquiring the sentiment orientations of each product feature. Hence, the available methods are not conducive to large-scale manual labeling of the sentiment orientations of each product feature. Moreover, previous studies on different fuzzy sets only represent information about each product feature rather than entire online product reviews. Since the q-ROFS can significantly characterize the complex information of comparing reviews for the same product on different platforms (Yang et al., 2020), we incorporate q-ROFS into our method to express the complexity of online product reviews. It is also important to ensure the integrity of complex information in online product reviews. The mass assignment (Shaheen et al., 2021) and BERT (Devlin et al., 2018) help complex information not to be lost. Hence, we also consider the mass assignment and BERT in our method to extract complex information from online product reviews.

To address the above-mentioned literature gaps, this study proposes a new product ranking method considering the mass assignment of features based on BERT and q-rung orthopair fuzzy set theory. Compared to existing product ranking methods, the proposed method does not involve a large amount of manual annotation cost and can characterize complex information of features from online product reviews. The key contributions of the proposed method are summarized in the following points:

(1) The sentiment orientation of online product reviews is identified based on BERT. Hence, it is not necessary to identify the sentiment orientation of online product reviews limited to a single product feature and the cost of manual annotation is reduced.

(2) A new relative frequency of each feature is calculated to represent the sentiment analysis results. Then, the sentiment analysis results are transformed into q-rung orthopair fuzzy numbers through mass assignment. Hence, the information of each feature of the product is represented using the q-rung orthopair fuzzy numbers.

(3) A new method for product ranking based on online product reviews is proposed based on the q-rung orthopair fuzzy generalized weighted Heronian mean operator (q-ROFGWHMO).

Therefore, using the proposed method in this paper, we can support the customers with the precise recommendation of suitable products during the shopping experience. Moreover, this research supports practitioners in accessing the sentiment orientation of online product reviews and not spending resources to label the sentiment orientations of multiple features. Hence, the cost of extensive manual data tagging is reduced for administrators.

The rest of this paper is organized as follows. Section 2 provides an overview of the related studies on product ranking methods, BERT, q-ROFS and mass assignment. Section 3 describes the five-step procedure of the proposed method for product ranking through online product reviews. Section 4 elaborates on feature mining and the sentiment orientation of online product reviews based on BERT. Then, section 5 shows the relative frequency and product ranking based on q-ROFS and mass assignment. In section 6, an empirical case study including six phones verifies the feasibility and validity of the proposed method. Finally, Section 7 presents the conclusions of this paper.

2. Related work and Preliminaries

Reviewing the related works allows us to identify not only the present study's contribution but also the elements of the available knowledge are relevant to the study's goals. Hence, a review of related work on product ranking methods, BERT, q-ROFS and mass assignment are presented.

We followed the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines to produce this review. PRISMA provides a standard peer methodology that uses a guideline checklist (Moher et al., 2015). Using PRISMA, we conducted a semi-structured literature review and searched two electronic databases (Web of Science and Scopus) between 1900 and 2022. Search terms were modified and combined with Boolean operators as following terms "product ranking method" AND "(online) reviews" AND "BERT" AND "q-Rung orthopair fuzzy set" AND "mass assignment". Hence, we searched 164,742 articles by title and abstract, and 52,942 articles have been selected. Assessing the full text of the articles, only 22 papers matched the topics of the product ranking method and were included in this paper.

2.1. Product ranking methods through online product reviews

Product ranking methods can obtain useful information from a large number of online product reviews in a short period of time and support the purchase decisions of consumers. To support consumers in ranking products, some studies describe methods to reflect consumer satisfaction through numeric ratings (Engler et al., 2015; Li et al., 2014; Parsons et al., 2021). Some of these studies focus on mining the features and sentiment orientations of features from online product reviews (Bi et al., 2019; Fu et al., 2020; Liu et al., 2017b,a; Peng et al., 2014; Yang et al., 2020; Zhang et al., 2020a), while other studies directly mine comparative sentences and relationships from online product reviews (Jindal & Liu, 2006; Xu et al., 2011; Zhang et al., 2010).

A numeric rating is merely a score, whereas an online product review is a comment with a more detailed description of sentiments regarding the product (Yang et al., 2016). Many scholars have studied product ranking methods in terms of online product reviews. Table 1 summarizes the research on product ranking methods that is closely related to three aspects of the current work. First, some studies discuss different methods for extraction of the features and the sentiment orientations related to each feature, such as tokenization, part-of-speech tagging, dictionary-based sentiment analysis. Second, some studies use different types of fuzzy sets to characterize features, such as IFSs, interval-valued Pythagorean fuzzy sets and q-ROFSs. Third, some studies use different methods to calculate the numerical value of each feature, such as domain experts and the frequency of the feature. For instance, Peng et al. (2014) introduced a fuzzy multicriteria decision-making approach to evaluate and rank competing products using online product reviews. The main advantage of the proposed method is that it can cope with subjective and uncertain online product reviews. Considering the neutral sentiment orientations of online product reviews, Liu et al. (2017b) proposed a method based on the sentiment analysis technique and intuitionistic fuzzy set theory to rank alternative products through online product reviews. Recently, Fu et al. (2020) considered the explicit and implicit product features in online product reviews and developed a product ranking method based on BiLSTM-CRF and interval-valued Pythagorean fuzzy sets. Yang et al. (2020) also proposed a product ranking method using BiLSTM-CRF and q-rung orthopair fuzzy interaction weighted Heronian mean operators. Qin et al. (2021) used the intuitionistic and hesitant fuzzy set and sentiment analysis to rank tourist attractions from online tourist reviews. Zhang et al. (2022) obtained the overall prospect values of each product to rank them based on the intuitionistic fuzzy TODIM method and sentiment analysis.

The existing research has addressed the problem of extracting multiple features concerning the low recall and high information loss and the representation of feature information through different types of mining methods and fuzzy sets. However, there are still some limitations (1) Most existing methods prefer to mine the sentiment localization of features rather than the emotional localization of online product reviews, which leads to missing complex information from online product reviews. (2) The frequency formulas proposed by most existing methods are based on the features of online product reviews and cannot characterize the complex information. To overcome mentioned limitations, we propose a new relative frequency, which is transformed into a q-ROFS using mass assignment. Moreover, conventional frequency computation process involves each feature's sentiment orientation, increasing the cost of manual labeling. Conversely, the proposed relative frequency involves only sentiment orientations of online reviews and features that lead to reducing manual labeling costs.

2.2. BERT

BERT is a pre-trained language model proposed by Devlin et al. (2018). Unlike the traditional unidirectional language models (left-to-right or right-to-left) (Peters et al., 2018; Radford et al., 2018), BERT is designed to pre-train

Table 1: Summary of related research on product ranking methods

Available research	Mining features and sentiment orientations methods	Types of fuzzy sets to characterize features	Methods for calculating the numerical value of features	Ranking approach	Case study
Jindal & Liu (2006)	Part of speech tagging	-	-	Supervised learning approach	Experiment
Zhang et al. (2010)	Feature-based product ranking technique, artificially created positive and negative words	-	-	Product graph	Digital camera and televisions
Xu et al. (2011)	Manual annotation	-	-	Two-level CRF	Case
Li et al. (2014)	-	-	-	Numeric rating	Movies
Peng et al. (2014)	Tokenization, part of speech tagging	Fuzzy set	Domain experts	Fuzzy PROMETHEE approach	Mobile phones
Engler et al. (2015)	-	-	-	Numeric rating	Cameras
Yang et al. (2016)	-	-	-	Numeric rating	Products
Zhang et al. (2016)	-	-	-	Numeric rating	Movies
Liu et al. (2017a)	Support vector machine, one-versus one strategy	Interval valued intuitionistic fuzzy set	Frequency	Interval-valued intuitionistic fuzzy TOPSIS method	Cars
Liu et al. (2017b)	Dictionary-based sentiment analysis	Intuitionistic fuzzy set	Frequency	Intuitionistic fuzzy weighted averaging operator, PROMETHEE II method	Cars
Ren et al. (2017)	-	-	-	Dual hesitant fuzzy VIKOR method	Mobile phones
Bi et al. (2019)	Support vector machine, one-versus one strategy	Interval type-2 fuzzy set	Frequency	Interval type-2 TOPSIS method	Cars
Çalı & Balaman (2019)	Part of speech tagging, lexicon-based sentiment analysis	Intuitionistic fuzzy set	Frequency	VIKOR method	Hotels
Yang et al. (2019)	Dictionary-based sentiment analysis, part of speech tagging	Intuitionistic fuzzy set	Frequency	Dynamic intuitionstic fuzzy multiple attribute group decision making	Mobile phones
Fu et al. (2020)	BiLSTM-CRF	Interval valued Pythagorean fuzzy set	Frequency	Interval valued Pythagorean fuzzy weighted Heronian mean	Mobile phones
Yang et al. (2020)	BiLSTM-CRF	q-Rung orthopair fuzzy set	Frequency	q-Rung orthopair fuzzy interaction weighted Heronian mean operator	Mobile phones
Zhang et al. (2020a)	Sentiment score calculation algorithm	-	-	Improved VIKOR	Cars
Zhang et al. (2020b)	Part of speech tagging	Hesitant fuzzy set	Sentiment score	Extended TODIM method	Mobile phones
Parsons et al. (2021)	-	-	-	Numeric rating	Novel popcorn varieties
Qin et al. (2021)	Aspect-level sentiment analysis	Intuitionistic and hesitant fuzzy set	Frequency	Intuitionistic and hesitant fuzzy TOPSIS method	Tourist attractions
Zeng et al. (2021)	-	-	-	Interactive genetic algorithm with an alternation ranking method	Customized sports shoes
Zhang et al. (2022)	Lexicon-based sentiment analysis	Intuitionistic fuzzy set	Frequency	Intuitionistic fuzzy TODIM method	Mobile phones
The proposed method in this study	BERT	q-Rung orthopair fuzzy set	Relative frequency, mass assignment	q-Rung orthopair fuzzy generalized weighted Heronian mean operator	Mobile phones

deep bidirectional representations from the unlabeled text by jointly conditioning on both the left and right contexts in all layers. Hence, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as named entity recognition (NER) and sentiment analysis (SA) (Leow et al., 2021; Pota et al., 2021; Yang et al., 2022). NER identifies named entities with specific meanings in the text, such as person, place, and organizational structure names in the corpus (Nadeau & Sekine, 2007). Although BERT has performed well and can be applied as a regular component in many natural language processing (NLP) tasks, it ignores the integration of knowledge information into language understanding. To solve this challenge, Liu et al. (2019) proposed RoBERTa based on BERT by changing the method of pre-training. Subsequently, Cui et al. (2021) proposed RoBERTa-wwm ext, which surpassed BERT and ERNIE in multiple tasks. The model was enhanced based on RoBERTa, using whole word masking (WWM) to expand the amount of training data. Moreover, SA is a widely used to complete NLP task to evaluate the sentiment orientation of a text unit. SA aims to extract structured opinions from unstructured text and discover their sentiment orientations (Cambria et al., 2017). The lack of large labeled datasets including online product reviews makes it difficult to utilize traditional unidirectional language models to understand their full potential for NER and SA. A promising solution is to initialize the parameter values of the pre-trained model with training samples and fine-tune these parameter values according to the downstream tasks. Accordingly, this study adopts RoBERTa-wwm-ext as a pre-training model to fine-tune the parameter values to support NER and SA.

2.3. q-Rung orthopair fuzzy set and mass assignment

The concept of q-ROFSs proposed by Yager (Yager, 2017) which is a generalization of IFSs (Atanassov, 1986) and Pythagorean fuzzy sets (PFSs) (Yager & Abbasov, 2013; Yager, 2014). The q-ROFSs are fuzzy sets in which the membership grades of the element x are pairs of values in the unit interval, $< \mu_A(x), \nu_A(x) >$, where one of the values indicates membership degree in the fuzzy set and the non-membership degree (Yager, 2017). A q-rung orthopair fuzzy number is an element of q-ROFS. For q-ROFSs, the membership grades need to satisfy the following conditions: $(\mu_A(x))^q + (\nu_A(x))^q \leq 1$, $\mu_A(x) \in [0,1]$, $\nu_A(x) \in [0,1]$ and $q \geq 1$, where the parameter q determines the range of information expression. As q increases, the range of information expression increases. Obviously, IFSs require the condition $\mu_A(x) + \nu_A(x) \leq 1$, and PFSs require the condition $(\mu_A(x))^2 + (\nu_A(x))^2 \leq 1$. It is clear that q-ROFSs further diminish the limitation of IFSs and PFSs related to membership grades. Therefore, compared to IFSs and PFSs, q-ROFSs provide a more elastic mining for online product reviews to represent the complex purchase decisions of customer.

Mass assignment theory, introduced by Baldwin (1994), established a general procedure for obtaining a fuzzy set (Zadeh, 1996) from an information system. Motivated by the approach of Baldwin, Szmidt et al. proposed an algorithm to generate IFSs (Atanassov, 1999) based on mass assignment theory (Szmidt &

Baldwin, 2006). This technique extracts membership and non-membership functions for IFSs from relative frequency distributions. Even though this method is useful and produces IFSs for several information systems, it does not yield IFSs in general. Shaheen et al. proposed a modified algorithm for generating q-rung orthopair fuzzy sets (Shaheen et al., 2021). Therefore, the mass assignment (Shaheen et al., 2021) is carried out in this paper to obtain q-ROFSs from online product reviews.

3. The challenges associated with product ranking

In this section, a clear definition of product ranking challenges is presented. Some terminologies used in this paper are also defined.

3.1. Problem definition

Assume that a consumer wants to buy a product such as a smart phone. A preliminary investigation helps to determine several acceptable alternative products. However, the consumer must make the right decision among the alternatives despite having limited knowledge and experience. The following notations are used to denote the sets and variables in this problem.

- $A = \{A_1, A_2, ..., A_n\}$: the set of n acceptable alternative products, where A_i denotes the ith acceptable alternative product, $i = 1, 2, \ldots, n$.
- $F = \{f_1, f_2, ..., f_k\}$: the set of k product features, where f_j denotes the jth product feature, $j = 1, 2, ..., k$.
- $OR = \{O_1, O_2, \ldots, O_n\}$: the set of numbers of online reviews for alternative product A_i, where O_i denotes the number of online product reviews $A_i, i = 1, 2, \ldots, n$.
- $D_{im} = (D^1_{im}, D^2_{im}, ..., D^k_{im})$: the m^{th} online review for alternative product A_i, where the m^{th} online review possesses k features, and D^j_{im} denotes the sentence concerning the k^{th} feature in the m^{th} online product review $A_i, i = 1, 2, \ldots, n, j = 1, 2, \ldots, k, m = 1, 2, \ldots, O_n$.

This study aims to solve these challenges to rank the alternative products $A_1, A_2, ..., A_n$ based on the online review D_{im}.

3.2. The proposed method for ranking alternative products using online product reviews

To solve the challenge mentioned in subsection 3.1, a novel method is proposed, as shown in Fig. 1. The novel method involves a five-step procedure:

(1) Collect the online reviews of alternative products using a web crawler,
(2) Mine the features and the sentiment orientations of the online reviews using BERT to obtain the relative frequency of alternative products for each product feature,

(3) Convert the relative frequencies of each feature to q-rung orthopair fuzzy numbers using mass assignment,
(4) Aggregate the q-rung orthopair fuzzy number of each alternative product through q-ROFGWHMO,
(5) Rank each alternative product by score or accurate function.

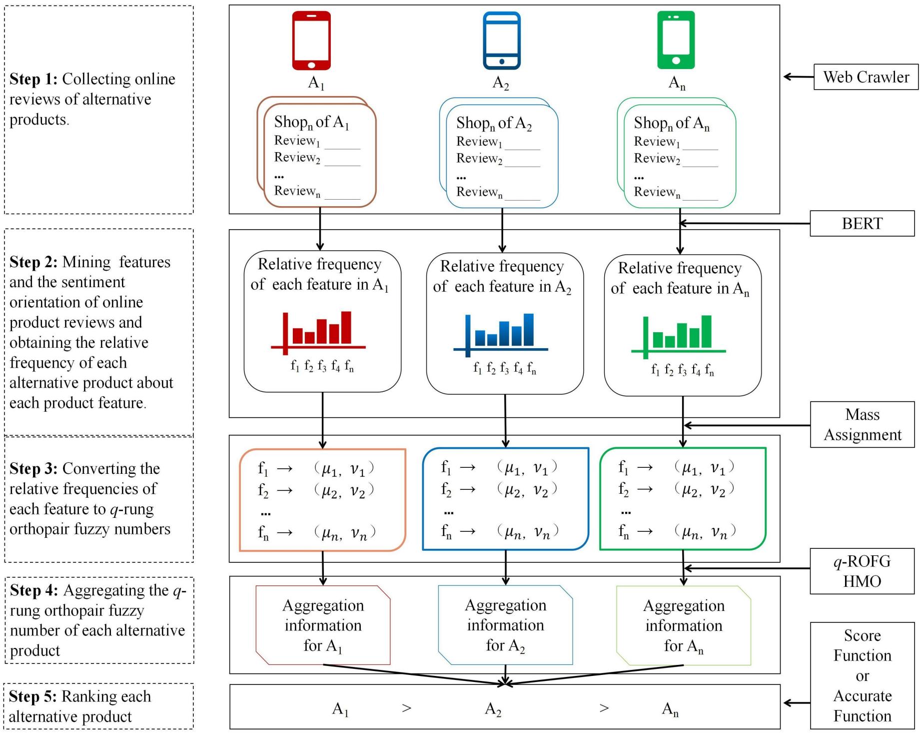

Figure 1: The five-step procedure of the proposed method

4. Feature mining and the sentiment orientation of online product reviews

In this section, we mine the features and sentiment orientation of online product reviews using pre-training and fine-tuning.

During pre-training, the RoBERTa-wwm-ext model (12-layer, 768-hidden, 12-heads) is selected as the pre-training model. During fine-tuning, the review data of each product are collected, as reported in Table 3. Moreover, 10% of online reviews for each product is randomly extracted from Taobao and JD.com, and the features and emotional positioning of the extracted reviews for each product are labeled manually. This paper utlizes the RoBERTa-wwm-ext pre-training model to fine-tune the review data using the human-labeled data. For the same product feature, customers can express their opinions using many various kinds of words or phrases. These words and phrases are domain synonyms, which need to be categorized under the same feature group. Based on available feature grouping solutions (Dahooie et al., 2021; Shieh & Yang, 2008; Zhang et al., 2022), the collected features of the mobile phone are categorized into nine features, including service, performance, appearance, photograph, screen, battery, price, network, and other functions. The human-labeled data for each online product review are used for fine-tuning the RoBERTa-wwm-ext model for NER and SA. The settings of the hyper-parameters in different downstream tasks are shown in Table 2.

Table 2: The settings of the hyper-parameters in different downstream tasks

Parameters	Vaule in NER	Vaule in SA
Batch size	16	16
Learning rate	4e-5	1e-5
Max epoch	1	2
Max sequence length	512	256

4.1. Feature extraction of online product reviews

Using the collected online product reviews, the explicit and implicit product features can be extracted. For example, in the review "the appearance of phone is very nice and works very smoothly", 'appearance' is the explicit feature, while 'smoothly' is implicitly represented by the performance of the product feature. In order to extract the features (Figure 3), the reviews are modeled as a sequence labeling task, where each word of the input is labeled as one of the three letters in $\{B-feature, I-feature, O\}$. Label '$B-feature$' stands for 'Beginning' of the product feature, '$I-feature$' stands for 'Inside' of the product feature, and 'O' for 'Outside' or no product features. Sequences of n words to be fed into the BERT architecture are represented as

$$[CLS], Word_1, Word_2, ..., Word_n, [SEP]$$

where the $[CLS]$ token is an indicator of the beginning of the sequence and its sentiment when performing sentiment classification. The $[SEP]$ token is a token for separating a sequence from the subsequent one. Finally, $Word_i$ are the words of the sequence. Using the BERT model, for each item of the sequence, a vector representation of the size 768 and the size of BERT's hidden layers are computed for each item of the sequence. Then, we apply a fully connected layer to classify each word vector as one of the three labels.

4.2. Sentiment orientation of online product reviews

Given the online product reviews, sentiment analysis aims to classify the sentiment orientation towards each online product review as positive or negative. In the SA task, the input format for the BERT model is the same as in NER. The $[CLS]$ token in the input representation (Figure 2) of the BERT in which the sentiment is encoded. After the input goes through the network and into the last layer, the sentiment is extracted from this token by applying a fully connected layer to its encoding.

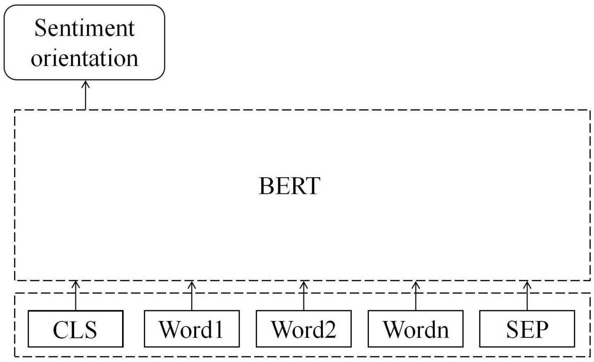

Figure 2: Extracting the emotional orientation of online product reviews based on BERT

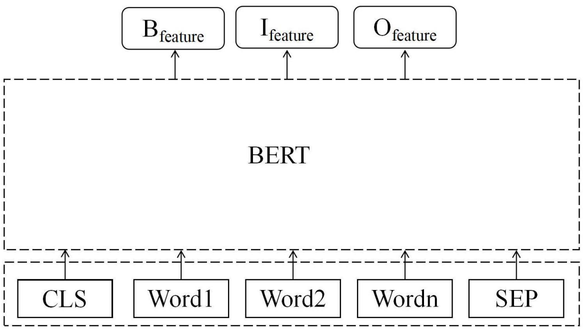

Figure 3: Extracting feature terms based on BERT

5. The relative frequency and ranking of products based on *q*-rung orthopair fuzzy sets

In this section, a novel approach for ranking the alternative products based on q-ROFSs is proposed. The approach includes the three following steps: (1) calculating the relative frequency of each alternative product concerning each product feature, (2) determining the q-rung orthopair fuzzy number of each alternative product concerning each product feature, and (3) aggregating the overall q-rung orthopair fuzzy number of each alternative product and ranking of the alternative products. Detailed descriptions of each step are given below.

Calculating the relative frequency of each alternative product concerning each product feature. Let A_i^j be the j^{th} feature of the i^{th} product, where $i = 1, 2, ..., n$ and $j = 1, 2, ..., k$. FRQ^{pos} and FRQ^{neg} are relative frequencies for positive and negative sentiment orientation, respectively. The values of FRQ^{pos} and FRQ^{neg} can be calculated by Eqs.1 and 2, respectively.

$$FRQ^{pos}(A_i^j) = \frac{\sum_{m=1}^{O_i} g_p(D_{im}^j)}{\sum_{m=1}^{O_i} f_p(D_{im})}, i = 1, 2, ..., n, j = 1, 2, ..., k. \tag{1}$$

$$FRQ^{neg}(A_i^j) = \frac{\sum_{m=1}^{O_i} g_n(D_{im}^j)}{\sum_{m=1}^{O_i} f_n(D_{im})}, i = 1, 2, ..., n, j = 1, 2, ..., k. \tag{2}$$

where f_p and f_n are two mapping functions that return a value of 1 when the sentiment orientation of the review is positive or negative, respectively. Otherwise, both functions return a value of 0. g_p and g_n are two mapping functions, which return a value of 1 when the sentiment orientation of the review is positive or negative with feature f_j, respectively. Otherwise, g_p and g_n return a value of 0.

Determining the q-rung orthopair fuzzy number of each alternative product concerning each product feature. To convert a relative frequency to a q-ROFS, Shaheen et al. (2021) suggested an algorithm established via possibility theory. Based on the relative frequencies of features and Theorem 1 in (Shaheen et al., 2021), let P^+ be the relative frequency of $FRQ^{pos}(A_i^j)$ in the nine feature sets Ω, taking as a range of values $\{p_1^+, p_2^+, ..., p_k^+\}$, where $0 \leq p_{k+1}^+ < p_k^+ \leq 1$ and $\sum_{j=1}^{k} p_j = 1$. We obtain the possibilities $POS^+(A_i^j) = |F_j|\, p_j^+ + \sum_{z=j+1}^{k} (|F_z| - |F_{z-1}|)p_z^+$, where $|F_j| = \{x \in \Omega \,|\, P(x) \geq p_j^+\}$. Let P^- be the relative frequency of $FRQ^{neg}(A_i^j)$ in the nine feature sets Ω, taking as a range of values $\{p_1^-, p_2^-, ..., p_k^-\}$, where $0 \leq p_{k+1}^- < p_k^- \leq 1$ and $\sum_{j=1}^{k} p_j = 1$. We obtain the possibilities $POS^-(A_i^j) = |F_j|\, p_j^- + \sum_{z=j+1}^{k} (|F_z| - |F_{z-1}|)p_z^-$, where $|F_j| = \{x \in \Omega \,|\, P(x) \geq p_j^-\}$. The membership degree, non-membership degree, and hesitate degree of features can be calculated by Eqs. 3-5 respectively.

$$\mu(A_i^j) = POS^+(A_i^j) - \pi(A_i^j) \tag{3}$$
$$\nu(A_i^j) = POS^-(A_i^j) - \pi(A_i^j) \tag{4}$$
$$\pi(A_i^j) = POS^+(A_i^j) - POS^-(A_i^j) \tag{5}$$

Aggregating the overall q-rung orthopair fuzzy number of each alternative product and ranking the alternative products. According to Definition 9 in (Wei et al., 2018),$q-ROFGWHM_w{}^{\phi,\varphi}(A_i^1, A_i^2, ..., A_i^k) = (\overset{k}{\underset{y=1}{\oplus}} \overset{k}{\underset{z=y}{\oplus}} (w_y w_z (A_y^k)^{\phi} \otimes (A_z^k)^{\varphi}))^{\frac{1}{\phi+\varphi}} = \left\langle (\sqrt[q]{1 - \prod_{y=1,z=y}^{k} (1-(\mu_i^y)^{q\phi}(\mu_i^z)^{q\varphi})^{w_y w_z}})^{\frac{1}{\phi+\varphi}}, \sqrt[q]{1-(1-\prod_{y=1,z=y}^{k}(1-(1-(\nu_i^y)^q)^{\phi}(1-(\nu_i^z)^q)^{\varphi})^{w_y w_z})^{\frac{1}{\phi+\varphi}}} \right\rangle = (\mu_i, \nu_j)$. Then, according to the score functions or accurate functions in (Liu & Liu, 2018) we can obtain the score values $S(A_i) = \mu_i^q - \nu_j^q$. We then use the values of the score function to rank the phones. If the score values from $S(A_i)$ are the same, the value of the accurate function $S(A_i) = \mu_i^q + \nu_j^q$ can be used to rank the phones.

6. Case study

In this section, a case study is used to illustrate the validity of the proposed method using online product reviews.

In recent years, many e-commerce platforms, such as Taobao and JD.com, have allowed consumers to share and obtain more product information through online reviews. Moreover, since consumers often have limited knowledge and expertise about mobile phones, it may be difficult for a consumer to choose a phone from the many different brands available. Considering the large number of online product reviews, consumers need recommendations. Hence, a novel product ranking method considering the mass assignment of features based on BERT and q-ROFGHMO is proposed to assist customers in making purchase decisions.

The customer wants to choose the suitable phone from among six alternative phones. The six alternative phones include the iPhone 13 (A_1), HUAWEI P50 (A_2), Mi 11 (A_3), vivo X60 (A_4), OPPO K9 (A_5) and Galaxy S21 (A_6). To select the desirable phone, we consider nine features of phones: service(C_1), performance(C_2), appearance(C_3), photograph(C_4), screen(C_5), battery(C_6), price(C_7), network(C_8) and, other functions(C_9). Meanwhile, the consumer provides the vector of weights of the nine features, i.e., $w = \{0.1, 0.1, 0.1, 0.2, 0.1, 0.1, 0.1, 0.1\}$. To support the purchase decision, this paper proposes a method for ranking six alternative phones. According to the process shown in Fig. 1 and the five-steps procedure given in Section 3, the computation processes and results are discussed below.

In the first step, the online reviews of mobile phone brands are obtained using web crawlers. Moreover, the online reviews of mobile phone brands are retrieved based on the release date of each mobile phone up to November 16, 2021. The statistical summary of online reviews for the mobile phones is presented in Table 3. The significant difference in the number of online reviews for different products is that some products have not been sold for a long time. For example, HUAWEI P50 was launched and sold in September 2021, and the data of online review for HUAWEI P50 was collected in November 2021. To ensure the accuracy of the model, data pre-processing was performed on the online reviews of the mobile phones, which included the omission of data such as repeated reviews, invalid reviews, and irregular characters. In the second step, the sentiment orientations and product features of online product reviews are calculated based on the relative frequency of each feature using Eqs. 1 and 2, as shown in Table 4. Table 4 presents the relative frequency of each feature for each phone brand. For example, the relative frequency for positive reviews is 0.22580, and the relative frequency for negative reviews is 0.60845 for the service feature of the iPhone 13. In the third step, we can translate the relative frequencies of features into q-rung orhthopair fuzzy numbers through mass assignment, as shown in Table 5. Table 5 presents the q-rung orthopair fuzzy number for each feature of the alternative phone brands. For example, the membership degree is 0.80845 and the non-membership degree is 0.95488 for the network feature of the iPhone 13. In the fourth step, we aggregate the nine features of each phone brand based on q-ROFGHMO. In the fifth step, we rank each phone brand by calculating the score value of each phone brand $S(A_i)$ in Table 8. Table 8 lists the score values of features for different methods. In the proposed method, the score value of the iPhone 13 is 0.18378, ($\phi = 0.6$, φ=1). Compared to other phone brands, the score and ranking of the iPhone 13 are the best.

Table 3: The statistical summary of online reviews of mobile phone brands

Phone brand	Taobao mall		JD mall		Total reviews
	Number of shops	Number of reviews	Number of shops	Number of reviews	
iPhone 13	5	3075	11	5278	8353
HUAWEI P50	10	3292	5	2743	6035
Mi 11	12	7401	13	11473	18874
vivo X60	9	6618	12	8831	15449
OPPO K9	11	7706	10	5252	12958
Galaxy S21	9	3684	7	7766	11450

6.1. Sensitivity analysis

In the sensitivity analysis, the q-ROFGHMO includes three parameters ϕ, φ and w, where ϕ and φ represent the degree of correlation between features and w represents the weight of the feature. These parameters may affect phone rankings. Two types of sensitivity analyses are conducted. First, we analyze the sensitivity of parameters ϕ and φ in order to change the ranking of the phones. Second, we examine the sensitivity of the feature's weight w to the ranking of the phone.

The impact results regarding the changes of the parameters ϕ and φ on the ranking of the phones are shown in Table 6. Table 6 shows that when $\phi = 0.1$,

Table 4: The relative frequency of each feature for each phone brand

Phone brand	Service(C_1)	Performance(C_2)	Appearance(C_3)	Photograph(C_4)	Screen(C_5)	Battery(C_6)	Price(C_7)	Network(C_8)	Other functions(C_9)
iPhone 13	(0.22580, 0.60845)	(0.22201, 0.11831)	(0.18486, 0.10423)	(0.10670, 0.00563)	(0.07128, 0.04789)	(0.06659, 0.01972)	(0.04827, 0.05634)	(0.00501, 0.02535)	(0.06948, 0.01408)
HUAWEI P50	(0.21478, 0.46587)	(0.22776,0.15870)	(0.18735, 0.05290)	(0.14298, 0.05973)	(0.18735, 0.05290)	(0.05067, 0.12457)	(0.02027, 0.01877)	(0.03435,0.04437)	(0.06562,0.04437)
Mi 11	(0.22235,0.36864)	(0.25471, 0.23812)	(0.13602, 0.02168)	(0.10366, 0.04295)	(0.08496, 0.07756)	(0.07171, 0.10967)	(0.04681, 0.03586)	(0.00985, 0.05129)	(0.06994, 0.05421)
vivo X60	(0.20034, 0.34524)	(0.21929, 0.17725)	(0.16720, 0.02513)	(0.18773, 0.07341)	(0.04998, 0.03902)	(0.06819, 0.21230)	(0.02983, 0.02447)	(0.01025, 0.05489)	(0.06720, 0.04828)
OPPO K9	(0.23105, 0.45714)	(0.29767, 0.16964)	(0.20157, 0.05893)	(0.11316, 0.01964)	(0.05239, 0.05714)	(0.02154, 0.09286)	(0.01121, 0.05714)	(0.01354, 0.03750)	(0.05787, 0.05000)
Galaxy S21	(0.16398, 0.33129)	(0.23023, 0.14630)	(0.15687, 0.06796)	(0.12313, 0.05663)	(0.13717, 0.08353)	(0.07991, 0.14677)	(0.03157, 0.06465)	(0.00738, 0.03917)	(0.06975, 0.06371)

Table 5: The q-rung orthopair fuzzy number of each feature for each phone brand with the value of q

Phone brand	Service(C_1)	Performance(C_2)	Appearance(C_3)	Photograph(C_4)	Screen(C_5)	Battery(C_6)	Price(C_7)	Network(C_8)	Other functions(C_9)	the value of q
iPhone 13	(0.00000, 0.00000)	(0.49014, 0.00379)	(0.51831, 0.07809)	(0.94930, 0.31257)	(0.69577, 0.45424)	(0.84225, 0.48059)	(0.66197, 0.60882)	(0.80845, 0.95488)	(0.88169, 0.46323)	7
HUAWEI P50	(0.00000, 0.01298)	(0.30717, 0.00000)	(0.59727,0.06784)	(0.56997, 0.20094)	(0.73549, 0.55734)	(0.37543, 0.59071)	(0.83106, 0.81760)	(0.63993, 0.70489)	(0.63993, 0.51038)	4
Mi 11	(0.00000, 0.03236)	(0.13053, 0.00000)	(0.80484, 0.20501)	(0.64178, 0.30210)	(0.48374, 0.37690)	(0.38741, 0.44316)	(0.69141, 0.61570)	(0.59174, 0.91139)	(0.57715, 0.45379)	3
vivo X60	(0.00000, 0.01894)	(0.20304, 0.00000)	(0.77447, 0.10577)	(0.51455, 0.04417)	(0.67725, 0.61007)	(0.13294, 0.50181)	(0.77976, 0.75110)	(0.58862, 0.90779)	(0.62169, 0.50676)	3
OPPO K9	(0.00000, 0.06662)	(0.28750, 0.00000)	(0.54286,0.12557)	(0.82321, 0.39081)	(0.55000,0.63936)	(0.44107, 0.82450)	(0.55000, 0.89912)	(0.68036, 0.88048)	(0.59286, 0.61196)	3
Galaxy S21	(0.00000, 0.06626)	(0.18546, 0.00000)	(0.43605, 0.08046)	(0.50779,0.19572)	(0.37376,0.13956)	(0.18452,0.41185)	(0.45257,0.74003)	(0.64748,0.93358)	(0.45824,0.47278)	4

φ=0.2, the ranking of the phones is $A_5 > A_1 > A_4 > A_3 > A_2 > A_6$, and the OPPO K9 ($A_5$) is the optimal choice. When $\phi = 0.3$, φ=0.6, the ranking of the phones is $A_1 > A_5 > A_4 > A_3 > A_2 > A_6$, and the iPhone 13 ($A_1$) is the optimal choice. These two results show different brands for the optimal choice. Moreover, we assume that the values of ϕ and φ are independent of each other. When $\phi = 1$, φ=0 or $\phi = 0$, φ=1, the ranking of the phones is $A_1 > A_5 > A_4 > A_3 > A_2 > A_6$ and $A_1 > A_4 > A_5 > A_3 > A_2 > A_6$, respectively. Furthermore, we increase the values of ϕ and φ. When $\phi = 5$, φ=9 or $\phi = 20$, φ=6, the ranking of phone is $A_1 > A_5 > A_4 > A_3 > A_2 > A_6$ and $A_1 > A_5 > A_3 > A_4 > A_2 > A_6$ respectively. Although the results of these optimal solutions are the same, the total rankings are completely different. Moreover, the values of ϕ, φ have a significant effect on the phone rankings.

The changes in feature weight w also affect the phone rankings. When $w = \{0.2, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1\}$, the customer pays more attention to the service (C_1) of phones. In this case, the ranking of phones is $A_4 > A_1 > A_5 > A_3 > A_2 > A_6$. In addition, when $w = \{0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.2, 0.1, 0.1\}$, the customer pays more attention to the price (C_7) of the phones. Then, the ranking of phone is $A_4 > A_1 > A_3 > A_5 > A_2 > A_6$. Hence, when customers focus on different features of the phones, the rankings of the phones are different.

In conclusion, the above analysis shows that the parameters ϕ, φ, and w in q-ROFGWHMO have a great impact on alternative ranking. Customers can adjust the parameters based on their own preferences to achieve reasonable results. Specifically, there is a certain relationship between the features; for example, the phone's price increases with its performance. Since the results of the optimal solutions remain the same as the parameter values of ϕ and φ increase, we can use simple integer values to reduce the computational complexity and capture the interrelationships between features. In addition, consumers express which the mobile phone feature they care about by changing the parameter w.

Table 6: The impact of ϕ, φ on the ranking of the phones.

The value of ϕ, φ	The ranking results of the phones
0.1, 0.2	$A_5 > A_1 > A_4 > A_3 > A_2 > A_6$
0.3, 0.6	$A_1 > A_5 > A_4 > A_3 > A_2 > A_6$
1, 0	$A_1 > A_5 > A_4 > A_3 > A_2 > A_6$
0, 1	$A_1 > A_4 > A_5 > A_3 > A_2 > A_6$
5, 9	$A_1 > A_5 > A_4 > A_3 > A_2 > A_6$
20, 6	$A_1 > A_5 > A_3 > A_4 > A_2 > A_6$

6.2. Research contribution in comparison with existing methods

The comparative analysis focuses on the accuracy of feature extraction, q-values, and ranking results to demonstrate the effectiveness and rationality of the method proposed in this paper.

As a multi-classification task, the sequence labeling task is transformed by NER using the micro average, which is the most appropriate evaluation metric (Liu et al., 2022). Table 7 summarizes the performance of different models based on feature extraction. According to Table 7, the BERT model is more effective in extracting features compared to the other models, such as BiLSTM (Huang et al., 2015), BiLSTM-CRF (Huang et al., 2015), and BERT-BiLSTM-CRF (Meng et al., 2022).

The q-ROFS expresses a wider range of information above online product reviews compared to the IFS and the PFS, which gives the customer comprehensive information to understand the phones. According to Table 5, the values for the network feature of the iPhone 13 (0.80845, 0.94588) are not allowable in IFS and PFS. Thus, the technique presented by Liu et al.(Liu et al., 2017b) fails to deliver an IFS.

Using the method proposed by (Fu et al., 2020) is used in the context described in this paper, the ranking results are $A_1 > A_5 > A_3 > A_2 > A_4 > A_6$. Moreover, using the method proposed in this paper, the ranking results are $A_1 > A_4 > A_5 > A_3 > A_2 > A_6$. Hence, the optimal result is A_1 and the worst alternative is A_6, which is consistent with the result of the proposed method in this paper and confirms the validity of our proposed method. Moreover, the difference in the overall ranking results can demonstrate the advantages of our proposed method.

The first advantage is the high accuracy of feature extraction in online product reviews. Compared with the BiLSTM-CRF model used by (Fu et al., 2020), the BERT model has higher accuracy in mining features and reduces the loss of mined features from online product reviews.

The second advantage is the lower cost of manual annotation. The product ranking methods proposed by (Fu et al., 2020; Yang et al., 2020) are based on the sentiment orientation of feature. However, the method proposed in this paper is based on the sentiment orientation of online product reviews and reduces manual annotation costs.

The third advantage is that q-ROFS well characterizes the complex information of online product reviews. The previous frequency formula proposed by (Fu et al., 2020; Qin et al., 2021; Yang et al., 2020; Zhang et al., 2022) cannot reflect the complex information of online product reviews. However, the method proposed in this paper reflects the complex information of online reviews through mass assignment and relative frequency formulas. Hence, the q-ROFS represents the complex information of online product reviews.

6.3. Practical implications

This study makes several practical contributions to serving the customers, industrial practitioners, and managers. First, the relative frequency involves the sentiment orientation of online product review and does not involve the sentiment orientations corresponding to the multiple features. Hence, the practitioners will access the sentiment orientation of online product review while do not need to invest in the sentiment orientation labeling of multiple features. Thus, the cost of extensive manual data tagging is reduced for managers.

Second, consumers express complex emotions and demands through online product reviews. The complex information can be extracted by relative frequency and mass assignments and characterized by q-ROFS. Therefore, the results can support the customers by precisely recommending of suitable products during the shopping experience. So, the consumers will have an easy and efficient shopping experience resulting in the right product selection.

Third, this method can be used by e-commerce platforms to recommend suitable phone products to consumers. This method supports the phone manufacturers to better understand the complex information expressed by consumers and to provide better services for the consumer. Moreover, the product ranking method proposed in this paper can effectively express the complex information of online product reviews and provide guidance for manufacturers' strategic decision-making.

Table 7: The micro-average feature extractions using different models

Phone brand	BiLSTM	BiLSTM-CRF	BERT-BiLSTM-CRF	BERT
iPhone 13	0.6865	0.7474	0.8020	**0.8660**
HUAWEI P50	0.7434	0.7460	0.7832	**0.8612**
Mi 11	0.8210	0.7979	0.8228	**0.9087**
vivo X60	0.7421	0.7632	0.8593	**0.9377**
OPPO K9	0.8498	0.8515	0.7706	**0.9728**
Galaxy S21	0.6726	0.7013	0.8054	**0.9087**

Table 8: The feature extraction score values for different methods

Phone brand	the method proposed by Fu et al.	proposed method
iPhone 13	0.20579	0.18378
HUAWEI P50	0.08845	0.10683
Mi 11	0.12553	0.13153
vivo X60	-0.80097	0.16458
OPPO K9	0.18221	0.16165
Galaxy S21	-0.89903	0.02862

7. Conclusions

The product ranking method can handle a large number of online product reviews to provide consumers with optimal product recommendations. The unstructured format of online product reviews and the complex emotional expression of customers make it difficult for product ranking methods to effectively express the information of online product reviews. In this study, online product reviews are crawled from Taobao and JD. Then, BERT is used to identify sentiment orientations and product features in the online product reviews. The concept of relative frequencies is proposed and do not involve the sentiment orientations corresponding to the features. Moreover, based on the relative frequencies of features, q-rung orthopair fuzzy numbers represent the performance of the alternative products in terms of the product features using mass assignment. Furthermore, the ranking of the alternative products is determined using the q-ROFGWHO, score function, or accurate function. The product ranking method can effectively represent the complex information about features from the reviews. Finally, the case study illustrates the use of the proposed method. Comparisons and sensitivity analyses are conducted to illustrate the characteristics and advantages of the proposed method. The product ranking method proposed in this paper reduces the cost of manual data labeling and can effectively characterize the complex information about features from the online product reviews. The product ranking method proposed in this paper reduces the cost of manual data labeling and can effectively characterize the complex information about features from the online product reviews. In addition, this proposed method applies BERT to ensure the integrity of the feature information compared with BiLSTM-CRF.

The limitation of this paper is that the proposed method has a long training time on the training samples despite the high accuracy in mining features from online product reviews. Future work seek to identify more advanced natural language processing techniques to mine product features from online reviews faster and more accurately and apply them to the development of real-time recommendation systems for customers.

CRediT authorship contribution statement

Songyi Yin: Formal analysis, Methodology, Software, Investigation, Writing-review & editing. **Yu Wang:** Supervision, Validation. **Sara Shafiee:** Writing-review & editing

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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References

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*, 87–96.

Atanassov, K. T. (1999). Intuitionistic fuzzy sets. In *Intuitionistic fuzzy sets* (pp. 1–137). Springer.

Baldwin, J. F. (1994). Mass assignments and fuzzy sets for fuzzy databases. In *Advances in the Dempster-Shafer theory of evidence* (pp. 577–594). Hoboken, NJ: John Wiley.

Bi, J.-W., Liu, Y., & Fan, Z.-P. (2019). Representing sentiment analysis results of online reviews using interval type-2 fuzzy numbers and its application to product ranking. *Information Sciences*, *504*, 293–307.

Çalı, S., & Balaman, Ş. Y. (2019). Improved decisions for marketing, supply and purchasing: Mining big data through an integration of sentiment analysis and intuitionistic fuzzy multi criteria assessment. *Computers & Industrial Engineering*, *129*, 315–332.

Cambria, E., Das, D., Bandyopadhyay, S., & Feraco, A. (2017). *A practical guide to sentiment analysis*. Springer,Cham,Switzerland.

Cui, Y., Che, W., Liu, T., Qin, B., & Yang, Z. (2021). Pre-training with whole word masking for chinese bert. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *29*, 3504–3514.

Dahooie, J. H., Raafat, R., Qorbani, A. R., & Daim, T. (2021). An intuitionistic fuzzy data-driven product ranking model using sentiment analysis and multi-criteria decision-making. *Technological Forecasting and Social Change*, *173*, 1–15.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Engler, T. H., Winter, P., & Schulz, M. (2015). Understanding online product ratings: A customer satisfaction model. *Journal of Retailing and Consumer Services*, *27*, 113–120.

Fan, Z.-P., Li, G.-M., & Liu, Y. (2020). Processes and methods of information fusion for ranking products based on online reviews: An overview. *Information Fusion*, *60*, 87–97.

Fu, X., Ouyang, T., Yang, Z., & Liu, S. (2020). A product ranking method combining the features–opinion pairs mining and interval-valued Pythagorean fuzzy sets. *Applied Soft Computing*, *97*, 1–17.

Huang, Z., Xu, W., & Yu, K. (2015). Bidirectional LSTM-CRF models for sequence tagging. arXiv preprint arXiv:1508.01991.

Jindal, N., & Liu, B. (2006). Identifying comparative sentences in text documents. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 244–251).

Leow, E. K. W., Nguyen, B. P., & Chua, M. C. H. (2021). Robo-advisor using genetic algorithm and BERT sentiments from tweets for hybrid portfolio optimisation. *Expert Systems with Applications*, *179*, 1–9.

Li, Y., Wu, C., & Luo, P. (2014). Rating online commodities by considering consumers' purchasing networks. *Management Decision*, *50*, 2002–2020.

Liu, P., Guo, Y., Wang, F., & Li, G. (2022). Chinese named entity recognition: The state of the art. *Neurocomputing*, *473*, 37–53.

Liu, P.-D., & Liu, J.-L. (2018). Some q-rung orthopai fuzzy Bonferroni mean operators and their application to multi-attribute group decision making. *International Journal of Intelligent Systems*, *33*, 315–347.

Liu, Y., Bi, J.-W., & Fan, Z.-P. (2017a). A method for ranking products through online reviews based on sentiment classification and interval-valued intuitionistic fuzzy TOPSIS. *International Journal of Information Technology & Decision Making*, *16*, 1497–1522.

Liu, Y., Bi, J.-W., & Fan, Z.-P. (2017b). Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory. *Information Fusion*, *36*, 149–161.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Meng, F., Yang, S., Wang, J., Xia, L., & Liu, H. (2022). Creating knowledge graph of electric power equipment faults based on BERT–BiLSTM–CRF model. *Journal of Electrical Engineering & Technology*, (pp. 1–10). https://doi.org/10.1007/s42835-022-01032-3.

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., & Stewart, L. A. (2015). Preferred reporting items for systematic review and meta-analysis protocols (prisma-p) 2015 statement. *Systematic reviews*, *4*, 1–9.

Nadeau, D., & Sekine, S. (2007). A survey of named entity recognition and classification. *Lingvisticae Investigationes*, *30*, 3–26.

Parsons, L., Rodriguez, O., & Holding, D. R. (2021). Improved taste and texture in novel popcorn varieties compared to conventional lines. *Journal of Sensory Studies*, *36*, 1–13.

Peng, Y., Kou, G., & Li, J. (2014). A fuzzy PROMETHEE approach for mining customer reviews in chinese. *Arabian Journal for Science and Engineering*, *39*, 5245–5252.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

Pota, M., Ventura, M., Fujita, H., & Esposito, M. (2021). Multilingual evaluation of pre-processing for BERT-based sentiment analysis of tweets. *Expert Systems with Applications*, *181*, 1–10.

Qin, Y., Wang, X., & Xu, Z. (2021). Ranking tourist attractions through online reviews: A novel method with intuitionistic and hesitant fuzzy information based on sentiment analysis. *International Journal of Fuzzy Systems*, *24*, 755–777.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding with unsupervised learning. Technical Report, OpenAI.

Ren, Z., Xu, Z., & Wang, H. (2017). Dual hesitant fuzzy VIKOR method for multi-criteria group decision making based on fuzzy measure and new comparison method. *Information Sciences*, *388*, 1–16.

Shaheen, T., Ali, M. I., & Toor, H. (2021). Why do we need *q*-rung orthopair fuzzy sets? some evidence established via mass assignment. *International Journal of Intelligent Systems*, *36*, 5493–5505.

Shieh, M.-D., & Yang, C.-C. (2008). Multiclass SVM-RFE for product form feature selection. *Expert Systems with Applications*, *35*, 531–541.

Szmidt, E., & Baldwin, J. F. (2006). Intuitionistic fuzzy set functions, mass assignment theory, possibility theory and histograms. In *2006 IEEE International Conference on Fuzzy Systems* (pp. 35–41). IEEE.

Wei, G., Gao, H., & Wei, Y. (2018). Some *q*-rung orthopair fuzzy Heronian mean operators in multiple attribute decision making. *International Journal of Intelligent Systems*, *33*, 1426–1458.

Xu, K., Liao, S. S., Li, J., & Song, Y. (2011). Mining comparative opinions from customer reviews for competitive intelligence. *Decision Support Systems*, *50*, 743–754.

Yager, R. R. (2014). Pythagorean membership grades in multicriteria decision making. *IEEE Transactions on Fuzzy Systems*, *22*, 958–965.

Yager, R. R. (2017). Generalized orthopair fuzzy sets. *IEEE Transactions on Fuzzy Systems*, *25*, 1222–1230.

Yager, R. R., & Abbasov, A. M. (2013). Pythagorean membership grades, complex numbers, and decision making. *International of Intelligent Systems*, *28*, 436–452.

Yang, N., Jo, J., Jeon, M., Kim, W., & Kang, J. (2022). Semantic and explainable research-related recommendation system based on semi-supervised methodology using bert and lda models. *Expert Systems with Applications*, *190*, 1–10.

Yang, X., Yang, G., & Wu, J. (2016). Integrating rich and heterogeneous information to design a ranking system for multiple products. *Decision Support Systems*, *84*, 117–133.

Yang, Z., Ouyang, T., Fu, X., & Peng, X. (2020). A decision-making algorithm for online shopping using deep-learning–based opinion pairs mining and q-rung orthopair fuzzy interaction heronian mean operators. *International Journal of Intelligent Systems*, *35*, 783–825.

Yang, Z., Xiong, G., Cao, Z., Li, Y., & Huang, L. (2019). A decision method for online purchases considering dynamic information preference based on sentiment orientation classification and discrete DIFWA operators. *IEEE Access*, *7*, 77008–77026.

Zadeh, L. A. (1996). Fuzzy sets. In *Fuzzy sets, fuzzy logic, and fuzzy systems: Selected papers by Lotfi A Zadeh* (pp. 394–432). World Scientific.

Zeng, D., He, M.-e., Zhou, Z., & Tang, C. (2021). An interactive genetic algorithm with an alternation ranking method and its application to product customization. *Human-centric Computing and Information Sciences*, *11*, 1–24.

Zhang, C., Tian, Y.-x., Fan, L.-w., & Li, Y.-h. (2020a). Customized ranking for products through online reviews: a method incorporating prospect theory with an improved vikor. *Applied Intelligence*, *50*, 1725–1744.

Zhang, D., Wu, C., & Liu, J. (2020b). Ranking products with online reviews: A novel method based on hesitant fuzzy set and sentiment word framework. *Journal of the Operational Research Society*, *71*, 528–542.

Zhang, K., Narayanan, R., & Choudhary, A. N. (2010). Voice of the customers: Mining online customer reviews for product feature-based ranking. (pp. 1–9). volume 10. https://doi.org/10.1109/JSTQE.2006.884785.

Zhang, M., Guo, X., & Chen, G. (2016). Prediction uncertainty in collaborative filtering: Enhancing personalized online product ranking. *Decision Support Systems*, *83*, 10–21.

Zhang, Z., Guo, J., Zhang, H., Zhou, L., & Wang, M. (2022). Product selection based on sentiment analysis of online reviews: An intuitionistic fuzzy TODIM method. *Complex & Intelligent Systems*, (pp. 1–14). https://doi.org/10.1007/s40747-022-00678-w.

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Highlights

- The product ranking methods based on online reviews have high costs and limitations.
- Sentiment orientations and product features are identified from reviews using BERT.
- A new relative frequency is computed to represent the sentiment analysis results.
- The results are converted to q-rung orthopair fuzzy numbers using mass assignment.
- A product ranking method is proposed based on generalized Heronian mean operator.

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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.