Online product decision support using sentiment analysis and fuzzy cloud-based multi-criteria model through multiple e-commerce platforms

Online Product Decision Support Using Sentiment Analysis and Fuzzy Cloud-based Multi-Criteria Model through Multiple E-Commerce Platforms

Zaoli Yang, Qin Li, Vincent Charles, Bing Xu, Shivam Gupta

***Abstract*—The competitive landscape of multiple e-commerce platforms and the vast amount of product reviews associated with these platforms have supported both consumers' online shopping decision making and also served as a reference for product attribute performance improvement. This paper proposes a sentiment-driven fuzzy cloud multi-criteria model for online product ranking and performance to provide purchase recommendations. In this novel model, Bi-directional Long Short-Term Memory Network-Conditional Random Fields (BiLSTM-CRF), sentiment analysis, and K-means clustering are first integrated to mine product attributes and compute sentiment values based on reviews from various platforms. Next, considering the confidence of the sentiment value, the cloud model is combined with q-rung orthopair fuzzy sets to define the new concept of the q-rung orthopair fuzzy cloud (q-ROFC) and the interaction operational laws between q-ROFCs are given. The sentiment values of each product attribute from different platforms are cross-combined and transformed into a type of q-ROFC, while multiple interactive information matrices are established. To investigate the correlation among homogeneous attributes, the q-ROFC interaction weighted partitioned Maclaurin Symmetric mean operator is proposed. Finally, we provide real-world examples of online mobile phone ranking and attribute performance evaluation. The results show that our proposed method offers significant advantages in dealing with customer purchase decisions for online products and problems with performance direction identification. Managerial implications are discussed.**

***Index Terms*—customer purchase decision; online product ranking; q-rung orthopair fuzzy cloud; sentiment mining of online reviews, multiple e-commerce platforms**

INTRODUCTION

THE successful development of e-commerce has reshaped people's lifestyles, with online shopping becoming the primary consumption mode for many consumers [1]. In 2021, global retail e-commerce sales have been approximately $5.2 trillion, which is expected to grow significantly and reaching ~$8.1 trillion by 2026[1]. During the online shopping process, consumers leave a large number of reviews on products sold through e-commerce platforms. For example, the Apple iPhone 11 Pro Max has 470,000 reviews on Jingdong (JD) Mall (https://www.jd.com). Such reviews have become the primary basis for consumers' purchasing decisions, as well as a valuable resource for businesses to evaluate their product performance and determine the direction of future product innovation [2-3]. However, due to the large number of reviews/comments across multiple e-commerce platforms, it is difficult for both users and enterprises to read them one by one, and hinders product decision support (e.g., product purchases) [4-5]. Therefore, it is crucial to develop a systematic product decision-making method based on online reviews generated by multiple e-commerce platforms.

Given Atanassov's intuitionistic fuzzy set [6] can simultaneously express positive, negative and neutral attitudes, several recent studies have aggregated these three sentiment tendencies of customer reviews in e-commerce platforms into the concept of intuitionistic fuzzy set (IFS) for product decision support [1,4]. Subsequently, few authors combined attribute sentiment analysis with different fuzzy sets, such as interval intuitive fuzzy set IFSs [4], type 2 fuzzy set [7] and probabilistic multivalued neutral language set [8], to support product decision-making. However, the above-mentioned methods neglected some important consumers' behaviour characteristics. To be more specific, due to the differences of e-commerce platforms, consumers need not only "products comparison", but also "platforms comparison" on the same product(s). Hence, product reviews from different e-commerce platforms will have an interactive impact on consumers' online purchase behavior. Meanwhile, errors might be passed to subsequent sentiment analysis due to factors such as uneven distribution of numbers of reviews on products and platforms, false reviews, among others. Consequently, the existing basic fuzzy set is difficult to accurately represent the three sentiment values of product reviews.

To deal with above problems, the cloud model is firstly introduced to examine the adverse effect of sentiment value errors, as shown in **Fig.1**. The cloud model transforms a qualitative concept into a quantitative value by considering the fuzziness, randomness of the concept and error interference [9]. Note that the quantitative value of a concept is a random value distributed around a central value, which can be applied

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[1] https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

to represent the error and confidence levels of sentiment value. Based on this, we introduce the cloud model for the first time into the q-rung orthopair fuzzy sets, define the q-rung orthopair fuzzy colud (q-ROFC) model. Then, we propose an interactive decision matrix based on q-ROFC, which is a combination of sentiment values across multiple platforms, to analyze the multi-platform comparison behavior of consumers in the online purchase process.

The main contributions of this paper include: (1) Building a product attribute mining algorithm that integrates bi-directional long short-term memory network-conditional random fields (BiLSTM-CRF), sentiment analysis technology and K-means clustering algorithm to accurately identify the sentiment tendency of reviews; (2) Defining the concept of q-ROFC to investigate the sentiment value error problem of product reviews; (3) Developing the q-ROFC interaction weighted partitioned Maclaurin Symmetric mean (*q*-ROFCIWPMSM) operator to aggregate the ROFC information; and (4) Proposing an online product decision framework integrating BiLSTM-CRF-based attribute mining with the q-ROFC-based multi-criteria model, which simulates the shopping comparison psychology of consumers in a multi-platform environment.

The rest of this article is organised as follows: Section 2 reviews the current state of research in attribute mining for online products, q-rung orthopair fuzzy sets (q-ROFSs), and methods for product decision-making based on online reviews. Section 3 details the data processing of product reviews. Section 4 lays out the method, including the q-ROFC model and an online product purchasing decision framework. Section 5 provides a real-world example of an online mobile phone purchase decision to demonstrate the effectiveness and benefits of the proposed method. Section 6 discusses the findings and provides a comparative analysis. Section 7 summarizes the conclusions and implications of the study.

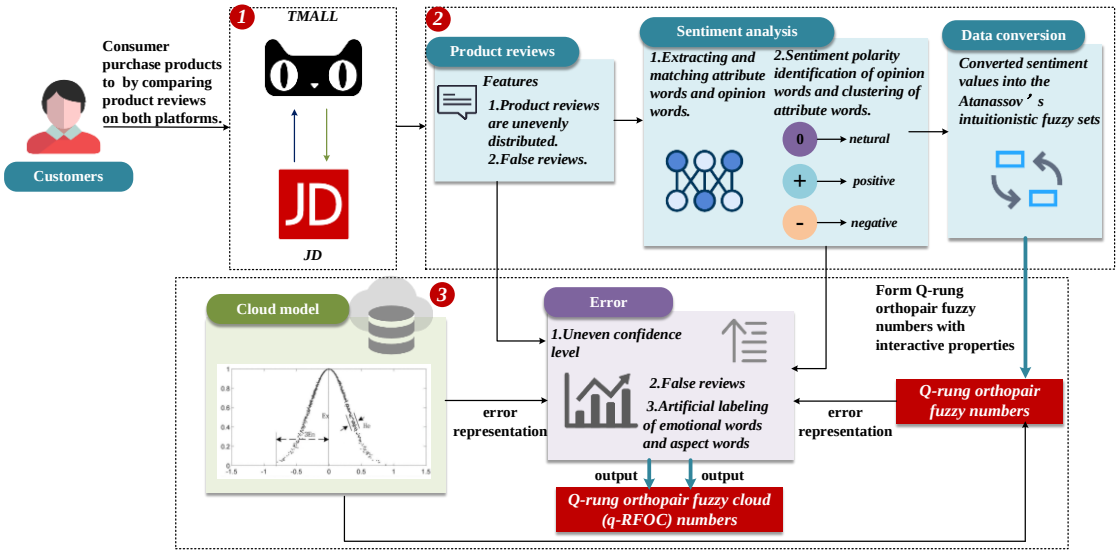

Fig.1. Cloud models are used to describe the errors of sentiment values.

II. LITERATURE REVIEW

In this section, we review the relevant studies from three main perspectives: attribute mining of online products, the q-rung orthopair fuzzy set, and approaches for product decisions based on online review mining.

A. Attribute sentiment mining for online products

Existing work on attribute sentiment mining of online products has mainly focused on the text mining of online reviews. The core task of this process is to extract the product attributes (features) and calculate their sentiment tendencies. The corresponding applied methods can be classified into three types: The first category considers product attribute mining to be a task of "keyword" extraction using unsupervised methods such as Latent Dirichelt Allocation (LDA), TextRank, and TF–IDF (Term Frequency–Inverse Document Frequency). Specifically, Chen *et al*. [10] developed a method for feature topic extraction and emotion computing in product reviews that integrates an order-preserving submatrix and TF–IDF. Zhao *et al*. [10] combined an aspect term extraction and aspect polarity classification for identifying the sentiment categories in online reviews. Turney [12] constructed an unsupervised learning algorithm that classified reviews into positive or negative based on the average emotional tendency of each phrase. The second approach involves the use of a dictionary or corpus, a window, a part of speech, a syntactic analysis, and/or other related methods. For example, Fan *et al*. [13] produced a systematic review and noted that existing studies are mainly based on using HowNet, WordNet, and other dictionaries to analyse product features and news reviews, or on building a new emotional vocabulary by introducing existing dictionaries to extract the opinions of online reviews and news reports in social media. Toosinezhad *et al*. [14] presented a dynamic window mechanism to integrate emotional computing and N-gram analysis to identify the nature of specific events reported on social media. The third category involves applying sequential labelling methods, including Hidden Markov Model

(HMM), Conditional Random Fields (CRF), Long Short-Term Memory Network (LSTM), and Support Vector Machines (SVM). For instance, Kalarani and Brunda [15] applied an HMM method to mark parts of speech and then integrated SVM and Artificial Neural Network (ANN) to build a synthetic algorithm for topic feature extraction and sentiment calculation. In addition, Akhtar *et al*. [16] combined CRF with maximum entropy and SVM to construct an emotional feature selection and classification method using Particle Swarm Optimisation (PSO). Furthermore, Chen *et al*. [17] and Phan *et al*. [18] built some comprehensive frameworks that combines BiLSTM-CRF (Bi-directional LSTM-CRF) and convolutional neural network (CNN) for sentence classification and sentiment discrimination.

B. The q-rung orthopair fuzzy set

Zadeh [19] first proposed the concept of fuzzy sets based on membership degree (MESD) in order to solve the problem of information representation for uncertain attributes. Subsequently, considering the limitations of MESD used to represent attribute information, Atanassov [6] developed the intuitionistic fuzzy set (IFS) based on Zadeh's fuzzy set. The description of uncertain attributes in an IFS was expanded from MESD—a single-dimensional decision element—to two dimensions, including MESD and the non-membership degree (NMESD), thus compensating for the shortcomings of Zadeh's fuzzy sets (which can only use the MESD to describe uncertain information). However, the IFS requires that the sum of the MESD and NMESD not be greater than 1, which restricts its application in practical complex decision-making problems. When the decision-maker independently evaluates the MESD and NMESD of one attribute, the sum of both may be greater than 1, thus making the IFS unable to process the attribute information. For example, if the decision-maker gives an MESD of 0.7 and NMESD of 0.8 for a certain attribute, then $0.7 + 0.8 > 1$, completely violating the operational conditions of IFS. In response to this phenomenon, Yager [20] defined the concept of the q-rung orthopair fuzzy set (q-ROFS), whose core idea is that the sum of the q^{th} ($q \geq 1$) powers of MESD and NMESD is less than 1. Compared to IFS, q-ROFS has greater flexibility and a wider range in its representation of attribute information. Some scholars have been constantly explored the operational laws and basic properties of q-ROFSs [21-22]. Other scholars have likewise presented new operational rules by embedding the Einstein operator, Hamacher operator, and Frank operator of the Archimedean paradigm into the q-ROFS [23-24]. Furthermore, some scholars have introduced classic aggregators into q-ROFS, developing the q-ROF Bonferroni mean (BM) operator [23, 25], q-ROF Maclaurin symmetric mean (MSM) operator [26-27]. These q-ROF operators are widely applied to deal with specific problems in various fields [28-29].

C. Product decision support based on online review mining

For product decision support methods based on online reviews, the general framework is to obtain product attribute features by mining online reviews, calculating the sentiment tendency of the attributes, converting the emotional value into an informative type of IFS, and, finally, constructing an emotional IFS-based product decision-making model. Representative works include that of Liu *et al*. [1], who conducted sentiment mining on related online reviews of certain cars by using the IFS to integrate the positive, negative, and neutral sentiment values of the car attributes and ultimately applied the intuitionistic fuzzy weighted average operator to obtain the product rankings. Meanwhile, Liu *et al*. [4] applied the concept of interval IFS to transform the three types of sentiment tendencies of attributes into interval IFS expressions and then used the fuzzy aggregation operator to calculate the rankings of products. Motivated by the ideas of Liu *et al*. [1], Zhang *et al*. [30] proposed a product preference recommendation model combining sentiment analysis and the fuzzy Kano model. Cali and Balaman [31] used the intuitionistic fuzzy decision-making framework based on sentiment computing to optimise the product supply and purchasing decision processes. Bi *et al*. [7] proposed an attribute sentiment representation method and product ranking model based on a type-2 fuzzy set. Furthermore, Ji *et al*. [8] combined a probabilistic multi-valued neutrosophic linguistic set to summarise the emotional tendency of product reviews and developed a sentiment-driven fuzzy decision support model. Similarly, Zhang *et al*. [32] and Qin *et al*. [33] constructed a product ranking framework based on hesitant fuzzy sets and sentiment analysis technology. Liang and Wang [34] developed a product decision support model by integrating product sentiment analysis and the intuitive language cloud model. Yang *et al*. [35] constructed an integrated method using intuitionistic fuzzy-based sentiment analysis for online hotel reservations. Yang *et al*. [36] and Yin *et al*. [37] presented a synthetic algorithm combining deep learning-based emotion mining and q-ROFS to support the online purchasing. Besides, Guo *et al*. [38] established a multiple criteria decision method for consumer preference analysis by integrating text mining and the rating of online reviews.

Existing studies have preliminarily established their online product decision-making frameworks based on online review mining and fuzzy set theory. However, the attribute mining of products in existing works does not consider the matching of product attribute words and opinion words, thus ignoring the sentiment calculations for some implicit attribute words. In addition, the operational rules and aggregation operators in q-ROFS are based on the Archimedean paradigm, which regards the MESD and NMESD in different decision elements as independent of each other without considering their correlations. In addition, existing studies either only use review data from a single e-commerce platform, or simply bundle data from multiple platforms without analysing the interactive impact of attribute sentiments from different platforms on product decision-making. Given the diverse development of e-commerce, to make optimal online

purchasing decisions, consumers tend to "compare products" as well as "compare platforms". Finally, the confidence level of the sentiment value is also ignored in existing studies, thus failing to consider the influence of different numbers of reviews or calculation errors on the sentiment calculation. This may not only reduce the accuracy of attribute word mining and its sentiment value but also neglect the decision-making behaviour characteristics of consumers, thus leading to unreasonable decision results. Therefore, to support the purchasing decisions of consumers and the improvement requirements of enterprises, it is necessary to develop an online product decision method that can improve the accuracy of attribute sentiment calculations and simulate the influence of multi-platform interactions.

III. DATA PROCESSING

To establish the product set $P=\{P_1,P_2,\cdots,P_m\}$, we used the Python-based Selenium crawler tool to obtain the reviews corresponding to m products from the Tmall (https://www.tmall.com/) and JD (https://www.jd.com/) online malls[2]. Note that Selenium is an automated testing tool for web applications. It can run directly on the browser and be used to simulate user operations on the browser. The webpage information is crawled by selenium with the help of Python. The specific process of capturing e-commerce website comments with the selenium module is shown in **Fig.2**.

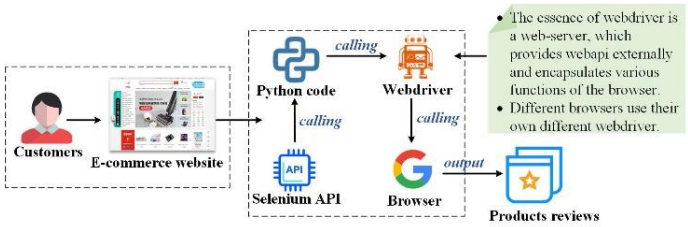

Fig.2. Selenium module running process diagram

The product attributes involved in the reviews on these two platforms are not automatically classified, so users need to screen such attributes themselves. Therefore, to obtain reasonable product attributes and corresponding opinions, it was necessary to extract and match product attribute words and opinion words, identify the sentiment polarity of opinions, and perform the clustering optimisation of attributes before finally converting the sentiment values into the corresponding expression structure with the type of q-ROFS. The specific steps of data processing were as follows:

(1) Extracting and matching product attribute words and corresponding opinion words. First, the problem of extracting attribute words and opinion words is modelled as a sequence labelling task, as shown in **Fig.3**. Then, a named entity recognition method based on BiLSTM-CRF [17] is constructed to identify the valid reviews about product $P_i\ (i=1,2,\cdots,m)$. Meanwhile, Jieba[3] was used for the word segmentation of reviews, to determine the position of each word in the sentence. The BIOES tagging model [39] is used to tag the entity after word segmentation, where B*# is the beginning of * (O: opinion, A: attribute) in P#, I indicates the inside, E is the end, S is single, and O signifies other words. An example of a labeled sentence is shown in TABLE I.

TABLE I
EXAMPLING OF LABELLING

Input	极	其	灵	活	,	系	统	稳	定	,
	(Extremely flexible)					(Stable ssystem)				
Label	BO1	BO2	BO 3	EO 1	O	BA 2	EA2	BO1	EO1	O
Input	价	格	是	可	以	被	接	受	的	.
	(Acceptable price)									
Label	BF3	EF3	O	O	O	O	O	O	O	O

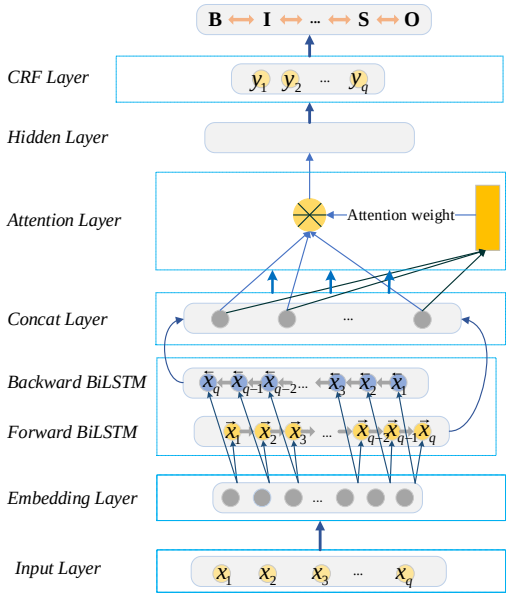

Fig.3. The process for extracting and matching product attribute words and the corresponding opinion words.

Next, each word in a review is randomly mapped to a word vector $x=\{x_1,x_2,\cdots,x_q\}$ in the input layer of the BiLSTM model to obtain the forward hidden layer vector $\vec{x}=\{\vec{x}_1,\vec{x}_2,\cdots,\vec{x}_q\}$ and backward hidden layer vector $\overleftarrow{x}=\{\overleftarrow{x}_1,\overleftarrow{x}_2,\cdots,\overleftarrow{x}_q\}$ of each word. Simultaneously, the two vectors are spliced together as the hidden layer of each word, which also represents the contact layer. Sigmoid is used as the activation function to calculate the probability of each word belonging to each label. Finally, the CRF [17] is used to examine the association between the tags, to input the tag sequence $y=(y_1,y_2,\cdots,y_q)$, and to determine the authenticity of the label. In the case analysis, we selected more than 31,000 reviews for manual annotation and more than 4,000 reviews as the test set. The overall accuracy of the model was 75.6%, the recall rate was 75%, and the F1 score was 65%, which indicates that the BiLSTM-CRF model can be effectively used

[2] https://github.com/Ruiver/OpinionExtractor

[3] https://github.com/fxsjy/jieba

to extract product attribute words and opinion words. We set the attribute set of product P_i as Attribute = (Attribute1, Attribute2, Attribute3, ..., Attribute*n*) and the opinion set as Opinion = (Opinion1, Opinion2, Opinion3, ..., Opinion*s*).

To extract product attribute words and opinion words, the idea of distance maximisation is used to match each attribute word in the attribute set with the opinion word(s) in the opinion set. The forward and backward LSTM layers are used to capture the semantic features and location features of the words in each review, while the attention weighted layer is used to identify the semantic content of important locations [40]. Then, the probability of an important position is determined by the distance maximisation model. In the end, whether or not the attribute–view pair AO = <Attribute, Opinion> matches can be determined by the probability value. Similarly, we selected more than 18,000 samples and labelled 10,000 of them as matching items and 8,000 as non-matching items. Then, we applied 2,000 and 1,000 test samples to test the matching and non-matching items, respectively. The test results showed that the accuracy of the model was 99%.

(2) Identifying sentiment polarity of opinion words and clustering attribute words. After determining the attribute and opinion word pair, it is necessary to determine the sentiment polarity of each opinion word and cluster a large number of attribute words into several comprehensive attributes of the product.

The identification of sentiment orientation in this paper involves the following two aspects:

(a) For the sentence-level opinion items, the sentiment analysis interface is provided by Baidu AIP[4], which can be directly invoked for sentiment polarity discrimination.

(b) For the phrase-level opinion items, we apply a Chinese NLP toolkit namely, the Stanford-chinese-corenlp[5]. We first analyze the part-of-speech (POS) characteristic of all the opinion terms. Then, a new sentiment dictionary is established by integrating the E-Chinese sentiment dictionary (ECSD)[6] and sentiment ontology library (SOL)[7]. The former is a specific vocabulary in the mobile phone domain, and the latter is a general domain vocabulary. The sentiment value (i.e., 0 for neutral, 1 for positive, and 2 for negative) of each word will be determined according to the order of ESCD, SOL, and labeled manually. With the help of POS tagging rules set and pre-established sentiment dictionary, the process of determined sentiment orientation of opinion units can be formulated. Finally, we obtain the sentiment polarity of the opinion words AO = <Attribute, Opinion, Sentiment polarity>. As shown in Algorithm 1. The sentiment tendencies of the attribute–opinion word pairs are recorded as positive sentiment AO^{pos}, negative sentiment AO^{neg}, and neutral sentiment AO^{neu}.

In addition, there are many attribute words with similar meanings and, so, the attribute words need to be clustered into several categories. For example, users usually describe the same features of phones with different phrases, such as "mobile phone box beautifully packaged", "responding to user questions in a timely manner", and "gift mobile phone decoration", which are used to describe the service features of a phone. Word2vec and K-means clustering algorithms [36] are used to cluster the attribute words into *N* categories, where each category is named according to the actual meaning of the attribute word, thus obtaining different attribute–opinion word pairs. The three types of sentiment values of the j^{th} attribute concerning the i^{th} product can be defined as AO_{ij}^{pos}, AO_{ij}^{neg}, and AO_{ij}^{neu} $(i=1,2,\cdots,m;\ j=1,2,\cdots,n)$, respectively, and the number of attribute–opinion pairs for the product P_i can be set as $AO_i=\{AO_{i1},AO_{i2},\cdots,AO_{in}\}$, where $AO_{ij}=(AO_{ij}^{pos},AO_{ij}^{neg},AO_{ij}^{neu})$ represents the sentiment value set of the j^{th} attribute of the i^{th} product.

Algorithm 1: Identification of sentiment orientation

Input: AO=<Attribute, Opinion>, sentiment dictionary
Process: Sentiment polarity identification
1: *Sentiment polarity = 0*
2: *If AO = 0 then*
3: *Sentiment polarity = 0*
4: *Else if AO = 1 then*
5: *Sentiment polarity =1*
6: *Else if AO = 2 then*
7: *Sentiment polarity =2*
Output: AO=<Attribute, Opinion, sentiment polarity>

(3) Data conversion: Based on the research of Liu *et al*. [1], the proportions of a number of different emotions for one attribute are calculated with respect to the e-commerce platform, following which the proportions are converted into the Atanassov's IFS [6], where the proportion of positive sentiments is MESD u_{ij}^{e}, the proportion of negative sentiments is NMESD v_{ij}^{e}, and that of neutral sentiments is the hesitancy degree (HMESD) τ_{ij}^{e}, as follows:

$$u_{ij}^{e}=\frac{AO_{e_{ij}}^{pos}}{AO_{e_{ij}}^{pos}+AO_{e_{ij}}^{neg}+AO_{e_{ij}}^{neu}}, \tag{1}$$

$$v_{ij}^{e}=\frac{AO_{e_{ij}}^{neg}}{AO_{e_{ij}}^{pos}+AO_{e_{ij}}^{neg}+AO_{e_{ij}}^{neu}}, \tag{2}$$

$$\tau_{ij}^{e}=\frac{AO_{e_{ij}}^{neu}}{AO_{e_{ij}}^{pos}+AO_{e_{ij}}^{neg}+AO_{e_{ij}}^{neu}}, \tag{3}$$

where $e=1,2,\cdots,k$ indicates the e^{th} e-commerce platform; $i=1,2,\cdots,m$ signifies the i^{th} product; and $j=1,2,\cdots,n$ represents the j^{th} attribute. We cross-combine the MESD and NMESD (or HMESD) from different platforms to form several new decision matrices with interactive characteristics, as shown in Equation (4):

$$R_{e,r}=\begin{bmatrix}\langle u_{11}^{e},v_{11}^{r}\rangle & \langle u_{12}^{e},v_{12}^{r}\rangle & \cdots & \langle u_{1n}^{e},v_{1n}^{r}\rangle\\ \langle u_{21}^{e},v_{21}^{r}\rangle & \langle u_{22}^{e},v_{22}^{r}\rangle & \cdots & \langle u_{2n}^{e},v_{2n}^{r}\rangle\\ \vdots & \vdots & \ddots & \vdots\\ \langle u_{m1}^{e},v_{m1}^{r}\rangle & \langle u_{m2}^{e},v_{m2}^{r}\rangle & \cdots & \langle u_{mn}^{e},v_{mn}^{r}\rangle\end{bmatrix},\begin{pmatrix}e=1,2,\cdots,k\\ r=1,2,\cdots,k\end{pmatrix} \tag{4}$$

[4] https://cloud.baidu.com/
[5] http://nlp.stanford.edu/software/stanford-chinese-corenlp-2018-02-27-models.jar
[6] https://github.com/zeitiempo/ECSD
[7] http://ir.dlut.edu.cn/

where $e, r = 1, 2, \cdots, k$ represent the e^{th} and r^{th} e-commerce platforms. If $e = r$, then $u_{ij}^{e} + v_{ij}^{r} \le 1$; however, if $e \ne r$, the decision information unit is composed of the MESD and NMESD from different platforms. Then, $u_{ij}^{e} + v_{ij}^{r} \ge 1$ and $(u_{ij}^{e})^{q} + (v_{ij}^{r})^{q} \le 1$. Therefore, treating $\langle u_{ij}^{e}, v_{ij}^{r} \rangle$ as a q-ROFS provides the foundation for the q-ROFS and cloud models presented in the following section.

IV. METHOD

A. The Concept of Q-rung Orthopair Fuzzy Cloud

In this section, we briefly review the definitions of a q-rung orthopair fuzzy (q-ROF) set and the cloud model. Then, we embed the cloud model into q-ROFS to develop the q-ROFC model.

Definition 1 [20]**.** Let T be a normal universe and $x \in T$. Then, we call:

$$A = \left\{ \langle x, \mu_A(x), \nu_A(x) \rangle \middle| x \in T \right\}$$

the q-ROF set, where $\mu_A(x)$ and $\nu_A(x)$ are the membership degree (MESD) and non-membership degree (NMESD) of x in T, respectively, and $\mu_A(x), \nu_A(x) \in [0,1]$. For convenience, $A = \langle \mu_A, \nu_A \rangle$ can be considered a q-ROF number (q-ROFN) that satisfies $0 \le \mu_A^q + \nu_A^q \le 1$. Then, $\pi_A(x) = 1 - (\mu_A^q + \nu_A^q)^{1/q}$ is the hesitancy membership degree (HMESD) of x in T.

Definition 2 [9]**.** Let R be a specific universe and G be a qualitative notation of R. If $x \in R$ is a stochastic exemplar of G that satisfies $x \sim N(Ex, En^2)$ and $En \sim N(En, He^2)$, then the certainty degree y of x related to G can be defined as the membership function, as follows:

$$y = e^{-\frac{(x-En)^2}{2En^2}},$$

which refers to a normal cloud on the distribution of x in R; further, (x, y) is called a cloud droplet.

The mathematical expectation *Ex*, entropy *En*, and hyper-entropy *He* are used to depict the qualitative properties of a notation in a cloud *H*. Then, $H = (Ex, En, He)$ can be presented as the cloud *H*. Essentially, *Ex* represents the center value of *G*, *En* signifies the uncertainty degree of *G* (or the dispersion degree of the cloud droplets), and *He* is the fuzziness of *En* (or the thickness of the cloud *H*).

The MESD and NMESD of q-ROFS are calculated using the attribute-based sentiment value according to Equation (4). However, the randomness and subjectivity of product reviews will lead to certain errors in the sentiment analysis of product reviews. It is mainly reflected in the following three aspects: First, given the number of attribute reviews are unevenly distributed on different products and platforms, this will lead to a higher (lower, respectively) confidence level for sentiment calculation for products with many (limited, respectively) reviews [4]. Secondly, fake reviews on various platforms and products can undermine the accuracy of review mining. Finally, certain errors can also occur during the stage of artificial labeling of sentiment words and attribute words in the sentiment analysis. These will lead to errors in sentiment value calculation. Therefore, based on the probability theory, we introduce a binomial distribution model [41] to measure the error and confidence level of sentiment analysis, so as to correct the sentiment value of the product attributes. At the same time, to investigate the approximate distribution of the error term; the binomial distribution model is also used to calculate the hyper-error term of the sentiment value. Finally, we obtain the error and hyper-error terms of the MESD and NMESD, whose expressions are given in Equations (5)–(8).

The calculation equation for the error term of the MESD is:

$$\omega_{u^e} = z_{\theta/2} \times \sqrt{\frac{\mu_{ij}^{e}(1-\mu_{ij}^{e})}{AO_{e_{ij}}^{pos} + AO_{e_{ij}}^{neg} + AO_{e_{ij}}^{neu}}}, \tag{5}$$

the calculation equation for the hyper-error term of the MESD is:

$$\varepsilon_{u^e} = z_{\theta/2} \times \sqrt{\frac{\omega_{u^e}(1-\omega_{u^e})}{AO_{e_{ij}}^{pos} + AO_{e_{ij}}^{neg} + AO_{e_{ij}}^{neu}}}, \tag{6}$$

the calculation equation for the error term of the NMESD is:

$$\omega_{v^r} = z_{\theta/2} \times \sqrt{\frac{v_{ij}^{r}(1-v_{ij}^{r})}{AO_{r_{ij}}^{pos} + AO_{r_{ij}}^{neg} + AO_{r_{ij}}^{neu}}}, \tag{7}$$

the calculation equation for the hyper-error term of the NMESD is:

$$\varepsilon_{v^r} = z_{\theta/2} \times \sqrt{\frac{\omega_{v^r}(1-\omega_{v^r})}{AO_{r_{ij}}^{pos} + AO_{r_{ij}}^{neg} + AO_{r_{ij}}^{neu}}}, \tag{8}$$

where $z_{\theta/2}$ represents the confidence level of the sentiment value of the product attribute and θ is the value of the confidence level. The value of $z_{\theta/2}$ can be obtained from the normal distribution.

According to the implications of the cloud model in Definition 2, the MESD u_{ij}^{e} and NMESD v_{ij}^{r} are represented as the positive sentiment expectation $Ex_{u_{ij}}^{e}$ and negative sentiment expectation $Ex_{v_{ij}}^{r}$, while the error and hyper-error terms of the MESD and NMESD are expressed as the entropy and hyper-entropy of the cloud model, respectively. Subsequently, we call:

$$a_{ij} = \left\langle \left(Ex_{u_{ij}}^{e}, En_{u_{ij}}^{e}, He_{u_{ij}}^{e} \right), \left(Ex_{v_{ij}}^{r}, En_{v_{ij}}^{r}, He_{v_{ij}}^{r} \right) \right\rangle \tag{9}$$

a q-ROFC, where $i = 1, 2, \cdots, m$; $j = 1, 2, \cdots, n$, and a_{ij} is the sentiment value-based q-ROFC of the j^{th} attribute of the i^{th} product.

B. Operational Interaction Rules Between the Q-ROFCs

As the decision unit with the form of q-ROFC is formed by the cross-combination of MESD and NMESD from different platforms, we next introduce an interactive relationship to define the operational laws between q-ROFCs. The idea of such an interactive relationship has been proposed and applied in IFSs by He *et al*. [42] and in Pythagorean fuzzy sets and

intuitionistic fuzzy soft sets by other authors [43-44], who proved that the idea of an interactive operation is more reasonable than traditional Archimedean paradigm-based operators in data operations with multiple structures, as the interaction operator can eliminate the adverse effects of some extreme values on the calculation results. Motivated by He *et al*. [42], we embed the interactive relationship idea into the q-ROFC environment to define the operational laws of interaction between q-ROFCs, as follows:

Definition 3. Let $a_1=\left\langle\left(Ex_{u_1},En_{u_1},He_{u_1}\right),\left(Ex_{v_1},En_{v_1},He_{v_1}\right)\right\rangle$ and $a_2=\left\langle\left(Ex_{u_2},En_{u_2},He_{u_2}\right),\left(Ex_{v_2},En_{v_2},He_{v_2}\right)\right\rangle$ be any two q-ROFCs, and let λ be a real number such that $\lambda\geq 0$. Then, the interaction operational laws of the q-ROFCs can be defined as follows:

$$a_1\oplus a_2=\left\langle\begin{pmatrix}\left(Ex_{u_1}^q+Ex_{u_2}^q-Ex_{u_1}^qEx_{u_2}^q\right)^{1/q},\\ \left(En_{u_1}+En_{u_2}\right),\left(He_{u_1}+He_{u_2}\right)\end{pmatrix},\right.$$
$$\left.\begin{pmatrix}\left(Ex_{v_1}^q+Ex_{v_2}^q-Ex_{v_1}^qEx_{v_2}^q-Ex_{v_1}^qEx_{u_2}^q-Ex_{v_2}^qEx_{u_1}^q\right)^{1/q},\\ \left(En_{v_1}+En_{v_2}\right),\left(He_{v_1}+He_{v_2}\right)\end{pmatrix}\right\rangle, \quad (1)$$

$$\lambda a=\left\langle\begin{pmatrix}\left(1-\left(1-Ex_u^q\right)^{\lambda}\right)^{1/q},\\ \lambda En_u,\lambda He_u\end{pmatrix},\right.$$
$$\left.\begin{pmatrix}\left(\left(1-Ex_u^q\right)^{\lambda}-\left(1-\left(Ex_u^q+Ex_v^q\right)\right)^{\lambda}\right)^{1/q},\\ \lambda En_v,\lambda He_v\end{pmatrix}\right\rangle. \quad (2)$$

According to He et al. [42], membership and non-membership in different decision units are aggregated through interactive operations to avoid homogeneous parallel operations between membership or non-membership degrees. As such, the Formula (1) can deal with the decision information formed by the information interaction of two original decision-making units. The aggregation results based on the above formulas can show the influence of interaction characteristics on the results. We use the following example 1 to illustrate that.

Example1.

Suppose a_1=<(0.812,0.008,0.002),(0.064,0.007,0.002)> and a_2=<(0.801,0.012,0.003),(0.083,0.01,0.003)> are two q-ROFCs, where q=3, then,

$$a_1\oplus a_2=\left\langle\begin{pmatrix}\left(0.812^3+0.801^3-0.812^3*0.801^3\right)^{1/3},\\ 0.008+0.012,0.002+0.003\end{pmatrix},\right.$$
$$\left.\begin{pmatrix}\left(0.064^3+0.083^3-0.064^3*0.083^3-\right.\\ \left.0.064^3*0.801^3-0.083^3*0.812^3\right)^{1/3},\\ 0.007+0.10,0.002+0.003\end{pmatrix}\right\rangle$$
$$=\left\langle(0.918,0.019,0.005),(0.073,0.016,0.006)\right\rangle$$

Definition 4 [42].Let $a=\left\langle\left(Ex_u,En_u,He_u\right),\left(Ex_v,En_v,He_v\right)\right\rangle$ be a q-ROFC, $\{(x_{u_1},y_{u_1}),(x_{u_2},y_{u_2}),\cdots,(x_{u_n},y_{u_n})\}$ be n cloud droplets in the MESD cloud $\left(Ex_u,En_u,He_u\right)$, and $\{(x_{v_1},y_{v_1}),(x_{v_2},y_{v_2}),\cdots,(x_{v_n},y_{v_n})\}$ be n cloud droplets in the MESD cloud $\left(Ex_v,En_v,He_v\right)$. Then, the score function of a c an be defined as:

$$G(a)=\frac{1}{n}\sum_{i=1}^{n}x_{u_i}y_{u_i}-\frac{1}{n}\sum_{i=1}^{n}x_{v_i}y_{v_i} \quad (10)$$

where $\frac{1}{n}\sum_{i=1}^{n}x_{u_i}y_{u_i}$ and $\frac{1}{n}\sum_{i=1}^{n}x_{v_i}y_{v_i}$ represent the expectations of clouds $\left(Ex_u,En_u,He_u\right)$ and $\left(Ex_v,En_v,He_v\right)$. Hence, the bigger the score value of a q-ROFC is, the better the q-ROFC will be. The example 2 are used to explain equation (10).

Example2.

Suppose $a=\left\langle(0.846,0.0073,0.0017),(0.062,0.0047,0.0014)\right\rangle$ is a q-ROFC, and $\begin{Bmatrix}(0.8504,0.9235),(0.8509,0.8359),\\ (0.8401,0.6132),(0.8527,0.7982)\end{Bmatrix}$ is four cloud droplets in the MESD cloud $(0.846,0.0073,0.0017)$

And $\begin{Bmatrix}(0.0650,0.9636),(0.0593,0.9487),\\ (0.0601,0.9521),(0.0702,0.7140)\end{Bmatrix}$ is four cloud droplets in the NMESD cloud $(0.062,0.0047,0.0014)$ .Then, the score of a can be calculated as:

$$G(a)=\left(\frac{1}{4}\right)*\begin{pmatrix}0.8504*0.9235+0.8509*0.8359+\\ 0.8401*0.6132+0.827*0.7982\end{pmatrix}$$
$$-\left(\frac{1}{4}\right)*\begin{pmatrix}0.0650*0.9636+0.0593*0.9487+\\ 0.0601*0.9521+0.0702*0.7140\end{pmatrix}$$
$$=0.6157$$

C. Q-ROFC Interaction Weighted Partitioned Maclaurin Symmetric Mean Operator

In this sub-section, the MSM operator is embedded into the q-ROFC environment to construct the q-ROFC interaction weighted partitioned Maclaurin Symmetric mean (q-ROFCIWPMSM) operator based on Definition 3.

Definition 5 [45]. Let $a_i\,(i=1,2,\cdots,n)$ be an ordinary real number and $k=1,2,\cdots,n$. Then:

$$MSM^{(k)}(a_1,a_2,\cdots,a_n)=\left(\frac{1}{C_n^k}\sum_{1\leq i_1\leq\cdots\leq i_k\leq n}\prod_{j=1}^{k}a_{i_j}\right)^{1/k} \quad (11)$$

is called the MSM operator, where $\left(i_1,i_2,\cdots,i_k\right)$ traverses all the k-tuple combinations of $\left(1,2,\cdots,n\right)$ and C_n^k is the binomial coefficient.

Considering attribute partitioning, we introduce the MSM operator to develop the q-ROFCIWPMSM as follows:

Definition 6. Let $a_i=\left\langle\left(Ex_{u_i},En_{u_i},He_{u_i}\right),\left(Ex_{v_i},En_{v_i},He_{v_i}\right)\right\rangle$ be a set of q-ROFCs. The attributes a_i are grouped into s categories, $H_1,H_2,\cdots,H_s$, with $H_i\cap H_j=\varnothing$ and $\cup_{u=1}^{s}H_u=n$. The parameter $k_1,k_2,\cdots,k_s$ is the k-tuple combination of each category and $k_u=1,2,\cdots,\left|H_u\right|$. Further, $\left|H_u\right|$ is the cardinality of $H_u\,(u=1,2,\cdots,s)$ and

$w_i (i = 1, 2, \cdots, n)$ is the weight of a_i, which satisfies $0 \le w_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$. We call:

$$q-ROCIWPMSM^{(k_1,k_2,\cdots,k_s)}(a_1, a_2, \cdots, a_n) = \frac{1}{s}\left(\sum_{u=1}^{s}\left(\frac{1}{C_{|H_u|}^{k_u}}\left(\sum_{\substack{i_1,i_2,\cdots,i_{k_u}\in H_u \\ 1\le i_1\le\cdots\le i_{k_u}}}\prod_{j=1}^{k_u}\left(n w_i a_{i_j}\right)\right)\right)^{1/k_u}\right) \quad (12)$$

the q-ROFCIWPMSM operator, n is the balance coefficient.

Theorem 1. Let $a_i = \left\langle \left(Ex_{u_i}, En_{u_i}, He_{u_i}\right), \left(Ex_{v_i}, En_{v_i}, He_{v_i}\right)\right\rangle$ be a collection of q-ROFCs and $w_i (i = 1, 2, \cdots, n)$ be the weight of a_i, such that $0 \le w_i \le 1$. Then, the value assembled by the q-ROFCIWPMSM operator is still a q-ROFC; that is,

$$q-ROCIWPMSM^{(k_1,k_2,\cdots,k_s)}(\tilde{a}_1, \tilde{a}_2, \cdots, \tilde{a}_n) = \frac{1}{s}\left(\bigoplus_{u=1}^{s}\left(\frac{1}{C_{|H_u|}^{k_u}}\left(\bigoplus_{\substack{i_1,i_2,\cdots,i_{k_u}\in H_u \\ 1\le i_1\le\cdots\le i_{k_u}}}\bigotimes_{j=1}^{k_u}\left(n w_i \tilde{a}_{i_j}\right)\right)\right)^{1/k_u}\right) \quad (13)$$

$$= \left\langle \left(Ex_u, En_u, He_u\right), \left(Ex_v, En_v, He_v\right)\right\rangle$$

We can easily prove that the equation (13) is true by mathematical induction.

Based on the above analysis, the detailed steps of the proposed method are as follows:

Step 1*: Python is applied to crawl related product reviews on multiple e-commerce platforms and apply the BiLSTM-CRF, sentiment analysis, and clustering algorithm to calculate the sentiment values of the attribute.*

Step 2*: Calculate the ratio of the three different sentiment values of each attribute for the e^{th} platform according to Equations (1)–(3) and convert them to the MESD u_{ij}^{e}, NMESD v_{ij}^{e}, and HMESD τ_{ij}^{e} of the IFS, respectively.*

Step 3*: Cross-combine the sentiment information of different platforms under the same attributes to obtain the q-ROFSs according to Equation (4).*

Step 4*: Construct multiple q-ROFC information decision matrices considering the confidence level of the attributes.*

Step 5*: Apply the interaction operational rule in Definition 3 to aggregate the multiple decision matrices to from a comprehensive decision matrix.*

Step 6*: Aggregate the a_{ij} into the synthetic a_i using the q-ROFCIWPMSM operator and draw the corresponding q-ROFC diagrams using the MATLAB software.*

Step 7*: Compute the overall expectations of MESD and of NMESD using the MATLAB software.*

Step 8*: Calculate the score value G(Pi) for a_i, according to Equation (10), and rank the alternatives based on their score values to obtain the final decision result.*

V. RESULT ANALYSIS

A consumer would like to purchase a mobile phone and, so, browses multiple e-commerce platforms. They wish to make a decision based on the relevant online reviews for the mobile phone. After preliminary investigations, seven mobile phones were selected as options; namely, Huawei_mate20 (P1), Iphone_XR (P2), Vivo_Z3 (P3), Xiaomi9 (P4), Galaxy_note9 (P5), Meizu16 (P6), and OPPO_R17 (P7). As these seven mobile phones are sold on two major e-commerce platforms in China, including Tmall (https://www.tmall.com/) and Jingdong (https://www.jd.com/), the consumer makes their final purchasing decision based on the sentiment values of attributes mined from relevant reviews from these two malls. Considering the completeness of the reviews and the richness of additional reviews, reviews of the above seven phones from November 2018 to July 2019 were crawled using web crawling technology, with 76,653 valid reviews from JD.com and 98,371 valid reviews from Tmall.com. The consumer can obtain their decision result using the proposed method, with the calculation process as follows.

A. *Calculation Process*

Step 1: Comprehensively utilise the BiLSTM-CRF, sentiment analysis, and clustering algorithm to obtain five attributes for evaluating the various phones—namely, exterior quality (C1), system operations (C2), camera function (C3), cost performance (C4), and service level (C5)—according to the actual meanings of the words being clustered. Let the weight vector of the five attributes be $w = \{0.2, 0.25, 0.15, 0.15, 0.25\}^T$. The numbers of the three types of sentiments for each attribute from Tmall and JD are shown in TABLES II and III.

TABLE II
THE NUMBER OF ATTRIBUTE SENTIMENTS ON JD.COM AND TMALL.COM

JD/Tmall	Sentiment polarity	Huawei_mate 20	Iphone_XR	Vivo_Z3	Xiaomi9	Galaxy_note9	Meizu16	OPPO_R17
Exterior quality	positive	11849/6296	5451/595	3725/943	7642/8571	1244/824	7747/1159	10786/4421
	negative	930/3602	566/482	331/710	606/5350	117/604	971/793	540/2121
	neutral	1810/11212	791/519	470/954	842/15825	225/1224	1309/2137	818/7005
System operation	positive	13730/6584	6855/697	4831/964	8724/10797	1296/1811	8713/1877	11484/4238
	negative	1082/3286	694/299	616/509	1066/3812	114/328	1391/615	915/1501
	neutral	2137/7042	950/698	873/1094	1313/14661	289/1451	1836/2083	1424/5322

Camera function	positive	6137/13048	2739/771	1769/1109	3750/16747	593/1121	3780/1853	5163/7634
	negative	696/6296	371/595	154/943	385/8571	65/824	672/1159	423/4421
	neutral	1462/3602	625/482	360/710	727/5350	160/604	1157/793	737/2121
Cost performance	positive	5660/11212	3010/519	1687/954	3555/15825	582/1224	3821/2137	4997/7005
	negative	883/6584	441/697	180/964	427/10797	74/1811	760/1877	413/4238
	neutral	1740/3286	839/299	474/509	881/3812	202/328	1449/615	852/1501
Service level	positive	13372/7042	7861/698	3197/1094	7810/14661	1042/1451	8088/2083	12244/5322
	negative	1095/13048	724/771	218/1109	701/16747	72/1121	1075/1853	752/7634
	neutral	1616/6296	787/595	399/943	808/8571	159/824	1192/1159	894/4421

Note: The left side of the slash shows data from JD.com and the right side shows data from Tmall.com

Step 2: Calculate the proportion of the three different sentiment values of the five attributes using Equations (1)–(3), and convert them to the MESD and NMESD.

Step 3: According to Equation (4), combine the sentiment values by step 2 interactively to obtain two new interaction matrices, as shown in TABLES III and IV.

Step 4: Considering the confidence of the sentiment value, introduce the cloud model to amend the sentiment information in step 2 and form the sentiment interaction matrix with the type of q-ROFC, as shown in TABLES III and IV.

TABLE III
DECISION INFORMATION GENERATED BY THE POSITIVE SENTIMENT VALUES ON JD.COM AND NEGATIVE SENTIMENT VALUES ON TMALL.COM.

	Exterior quality	**System operation**	**Camera function**	**Cost performance**	**Service level**
Huawei_mate20	<0.812, 0.0078, 0.0018; 0.076, 0.0072, 0.0023>	<0.81, 0.0073, 0.0016; 0.078, 0.0063, 0.0019>	<0.74, 0.0016, 0.0028; 0.08, 0.0086, 0.0029>	<0.683, 0.0123, 0.0029; 0.105, 0.0096, 0.0031>	<0.831, 0.0071, 0.0013; 0.07, 0.0056, 0.0016>
Iphone_XR	<0.801, 0.117, 0.0031; 0.101, 0.0105, 0.0035>	<0.807, 0.0103, 0.0023; 0.09, 0.0084, 0.0038>	<0.733, 0.0174, 0.0052; 0.116, 0.0136, 0.0049>	<0.702, 0.0168, 0.0047; 0.125, 0.0129, 0.0044>	<0.839, 0.0092, 0.0024; 0.104, 0.0077, 0.0022>
Vivo_Z3	<0.823, 0.0137, 0.0042; 0.041, 0.0042, 0.0014>	<0.764, 0.0129, 0.0034; 0.064, 0.0043, 0.0016>	<0.775, 0.0211, 0.0072; 0.049, 0.0057, 0.002>	<0.721, 0.0223, 0.0074; 0.051, 0.0059, 0.002>	<0.838, 0.0144, 0.0046; 0.038, 0.0035, 0.0011>
Xiaomi9	<0.841, 0.0093, 0.0024; 0.085, 0.0074, 0.0023>	<0.786, 0.0094, 0.0022; 0.125, 0.0066, 0.0024>	<0.771, 0.0145, 0.0041; 0.102, 0.0096, 0.0031>	<0.731, 0.0153, 0.0042; 0.12, 0.0107, 0.0034>	<0.838, 0.0092, 0.0024; 0.092, 0.0068, 0.0019>
Galaxy_note9	<0.784, 0.0249, 0.0094; 0.073, 0.0098, 0.0037>	<0.763, 0.0249, 0.0091; 0.069, 0.0089, 0.0047>	<0.725, 0.0376, 0.016; 0.096, 0.0151, 0.0062>	<0.678, 0.0384, 0.0158; 0.108, 0.0164, 0.0067>	<0.819,0.026, 0.0108; 0.072, 0.0104, 0.0041>
Meizu16	<0.773, 0.101, 0.0024; 0.079, 0.0069, 0.0021>	<0.73, 0.0098, 0.0022; 0.08, 0.0048, 0.0019>	<0.674, 0.0151, 0.0039; 0.078, 0.0078, 0.0026>	<0.634, 0.015, 0.0038; <0.112, 0.0111, 0.0037>	<0.781, 0.0098, 0.0023; 0.06, 0.006, 0.0019>
OPPO_R17	<0.888, 0.0069, 0.0018; 0.052, 0.0044, 0.0013>	<0.831, 0.0077, 0.0018; 0.057, 0.004, 0.015>	<0.817, 0.0117, 0.0033; 0.072, 0.0064, 0.002>	<0.798, 0.0122, 0.0033; 0.078, 0.0067, 0.002>	<0.881, 0.0066, 0.0017; 0.056, 0.0038, 0.001>

TABLE IV
DECISION INFORMATION GENERATED BY THE NEGATIVE SENTIMENT VALUES ON JD.COM AND POSITIVE SENTIMENT VALUES ON TMALL.COM.

	Exterior quality	**System operation**	**Camera function**	**Cost performance**	**Service level**
Huawei_mate20	<0.804, 0.0108, 0.0028; 0.064, 0.0049, 0.0014>	<0.812, 0.0092, 0.0022; 0.064, 0.0045, 0.0012>	<0.764, 0.0135, 0.0036; 0.084, 0.0073, 0.0023>	<0.704, 0.0144, 0.0037; 0.107, 0.0082, 0.0024>	<0.812, 0.0085, 0.002; 0.068, 0.0048, 0.0013>
Iphone_XR	<0.751, 0.015, 0.0042; 0.083, 0.0081, 0.0026>	<0.793, 0.0119, 0.0032; 0.082, 0.0072, 0.022>	<0.662, 0.0201, 0.006; <0.099, 0.0188, 0.0043>	<0.646, 0.0187, 0.0053; 0.103, 0.0112, 0.0039>	<0.801, 0.01, 0.0025; 0.077, 0.0066, 0.002>
Vivo_Z3	<0.884, 0.0069, 0.0018; 0.073, 0.0093, 0.0034>	<0.825, 0.0066, 0.0014; 0.097, 0.009, 0.0029>	<0.853, 0.0094, 0.0026; <0.067, 0.0127, 0.0056>	<0.812, 0.0104, 0.0027; 0.077, 0.0133, 0.0057>	<0.897, 0.0055, 0.0014; 0.057, 0.0091, 0.0037>
Xiaomi9	<0.799, 0.0106, 0.0027; 0.067, 0.0063, 0.002>	<0.745, 0.0087, 0.0019; 0.096, 0.0067, 0.0019>	<0.736, 0.014, 0.0037; 0.079, 0.0093, 0.0033>	<0.667, 0.0156, 0.0041; 0.088, 0.0098, 0.0034>	<0.806, 0.0093, 0.0022; 0.075, 0.0066, 0.002>
Galaxy_note9	<0.803, 0.015, 0.0046; 0.074, 0.0158, 0.0076>	<0.802, 0.0139, 0.0041; 0.067, 0.0146, 0.007>	<0.675, 0.0239, 0.0078; 0.079, 0.0228, 0.0126>	<0.655, 0.0252, 0.0083; 0.086, 0.0231, 0.0124>	<0.794, 0.0162, 0.0051; 0.057, 0.0156, 0.0084>
Meizu16	<0.797, 0.0103, 0.0026; 0.097, 0.0071, 0.002>	<0.806, 0.0071, 0.0015; 0.116, 0.0071, 0.0018>	<0.774, 0.0122, 0.0032; 0.12, 0.0104, 0.0033>	<0.629, 0.0169, 0.0045; 0.126, 0.0103, 0.0031>	<0.842, 0.0091, 0.0024; 0.104, 0.0072, 0.002>
OPPO_R17	<0.874, 0.0065, 0.0016; 0.044, 0.0045, 0.0015>	<0.849, 0.0061, 0.0013; 0.066, 0.0051, 0.0015>	<0.81, 0.0097, 0.0024; 0.067, 0.0076, 0.0026>	<0.77, 0.0105, 0.0025; 0.066, 0.0076, 0.0026>	<0.872, 0.0055, 0.0012; 0.054, 0.0046, 0.0014>

Step 5: To ensure the interactivity of the platform, we use the interaction operational rules in Definition 3 to further aggregate the interaction sentiment information in TABLES III and IV. In the aggregation process, we set the equal weight is set for each platform to reflect the same influence of the platform on the decision-making. Finally, a comprehensive decision matrix is formed as shown in TABLE V.

TABLE V.
COMPREHENSIVE DECISION MATRIX.

	Exterior quality	System operation	Camera function	Cost performance	Service level
Huawei_mate20	<0.808, 0.0093, 0.0023; 0.07, 0.006, 0.0018>	<0.811, 0.0082, 0.0019; 0.072, 0.0054, 0.0015>	<0.752, 0.0125, 0.0032; 0.082, 0.008, 0.0026>	<0.694, 0.0133, 0.0033; 0.106, 0.0089, 0.0027>	<0.822, 0.0078, 0.0018; 0.069, 0.0052, 0.0015>
Iphone_XR	<0.778, 0.0134, 0.0037; 0.093, 0.0093, 0.0031>	<0.8, 0.0111, 0.0029; 0.086, 0.0078, 0.003>	<0.701, 0.0188, 0.0056; <0.109, 0.0127, 0.0046>	<0.676, 0.0178, 0.005; 0.116, 0.0121, 0.0041>	<0.821, 0.096, 0.0024; 0.094, 0.0072, 0.0021>
Vivo_Z3	<0.857, 0.0103, 0.003; 0.064, 0.0068, 0.0024>	<0.797, 0.0097, 0.0024; 0.086, 0.0066, 0.0022>	<0.819, 0.00152, 0.0049; <0.061, 0.0092, 0.0038>	<0.773, 0.0164, 0.005; 0.068, 0.0096 0.0039>	<0.872, 0.01, 0.003; 0.051, 0.0063, 0.0024>
Xiaomi9	<0.821, 0.0099, 0.0026; 0.078, 0.0068, 0.0021>	<0.767, 0.0091, 0.002; 0.113, 0.0067, 0.0021>	<0.755, 0.0143, 0.0039; 0.093, 0.0095, 0.0032>	<0.701, 0.0154, 0.0042; 0.107, 0.0102, 0.0034>	<0.823, 0.0092, 0.0023; 0.085, 0.0067, 0.002>
Galaxy_note9	<0.794, 0.0199, 0.007; 0.073, 0.0128, 0.0056>	<0.783, 0.0194, 0.0066; 0.068, 0.0117, 0.0058>	<0.702, 0.0308, 0.0119; 0.089, 0.0189, 0.0094>	<0.667, 0.0318, 0.0121; 0.099, 0.0198, 0.0095>	<0.807, 0.0211, 0.0079; 0.066, 0.013, 0.0062>
Meizu16	<0.785, 0.0102, 0.0025; 0.089, 0.007, 0.0021>	<0.772, 0.0084, 0.0018; 0.104, 0.006, 0.0019>	<0.731, 0.0136, 0.0036; 0.106, 0.0091, 0.0029>	<0.631, 0.0159, 0.0041; 0.12, 0.0107, 0.0034>	<0.815, 0.0095, 0.0024; 0.09, 0.0066, 0.002>
OPPO_R17	<0.881, 0.0067, 0.0017; 0.049, 0.0044, 0.0014>	<0.84, 0.0069, 0.0016; 0.062, 0.0045, 0.0015>	<0.813, 0.0107, 0.0029; 0.069, 0.007, 0.0023>	<0.785, 0.0114, 0.0029; 0.073, 0.0071, 0.0023>	<0.877, 0.0061, 0.0014; 0.055, 0.0042, 0.0012>

Step 6: Apply the Equation (13) to aggregate the decision information to synthetic q-ROFCs with attribute dimensions. In addition, we segment the five attributes into two groups according to their practical significance (*i.e.*, exterior quality, system operation, and camera function are treated as group 1, while cost performance and service level are regarded as group 2). In this way, we can set K1 = 2 and K2 = 1. To deal with the interactive sentiment information and decision matrix, as well distinguish the traditional IFS from the q-ROFC, we set q=3 in Equation (13) and thereby obtain the comprehensive values of the five alternatives, as follows:

Huawei_mate20 =<(0.791, 0.0098, 0.0024), (0.079, 0.005, 0.0015)>,

Iphone_XR =<(0.7759, 0.0132, 0.0036), (0.0984, 0.008, 0.0025)>,

Vivo_Z3=<(0.834, 0.0118, 0.0035), (0.066, 0.006, 0.0021)>,

Xiaomi9=<(0.7856, 0.0111, 0.0028), (0.0954, 0.006, 0.0018)>,

Galaxy_note9=<(0.7682, 0.0238, 0.0088), (0.0774, 0.013, 0.0051)>,

Meizu16=<(0.7664, 0.0111, 0.0028), (0.1002, 0.006, 0.0017)>,

OPPO_R17=<(0.8496, 0.0079, 0.002), (0.0609, 0.004, 0.0013)>.

We used the MATLAB to draw q-ROFC diagrams of five alternatives. To avoid redundancy, we take Huawei_mate20 as an example here, where the number of cloud droplets was set to 2000. The visualisations are shown in **Fig. 4-8**.

It can be seen, from **Fig.4**, that the MESD cloud drop distribution was located on the left of the NMESD cloud drop for Huawei_mate20, which indicates that the positive sentiment for the Huawei_mate20 was obviously higher than the negative sentiment. The situation of the cloud drop distribution is consistent with the characteristics of the MESD value being bigger than NMESD value for the Huawei_mate20. In addition, as shown in **Figs. 5 and 6**, the thickness of the NMESD cloud droplets was larger than that of the MESD cloud droplets; that is, the NMESD cloud droplets were more scattered, indicating that the error of the Huawei_mate20 positive sentiment value is lower, while the corresponding confidence level was higher.

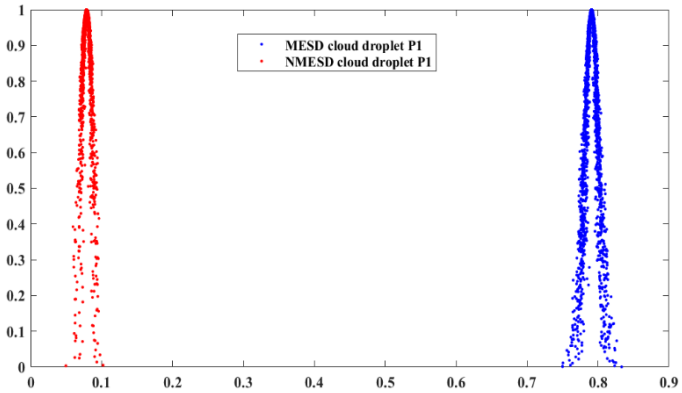

Fig.4. The cloud droplet distribution of Huawei_mate20 (P1).

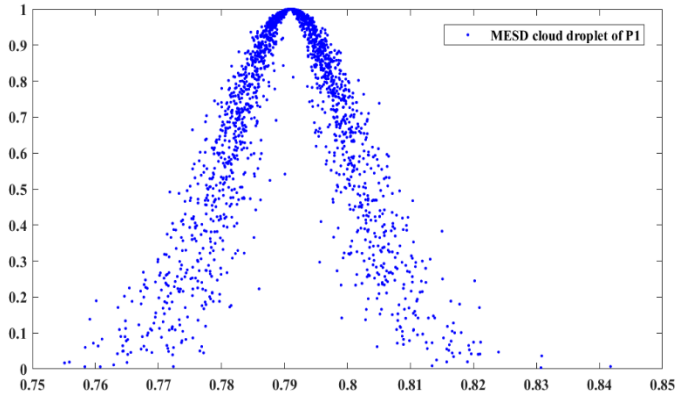

Fig.5. The MESD cloud droplet distribution of Huawei_mate20 (P1).

We can depict the cloud droplet distribution graphs of the other six alternative phones, omitting here.

The cloud droplet distributions of the other six products had similar characteristics to that of the Huawei_mate20: The cloud droplet of the positive sentiment was always distributed to the left of the negative sentiment, which indicates that the positive sentiment always has a greater advantage. Intuitively, the thickness degree of the MESD and NMESD cloud droplets

for Galaxy_note9 in **Fig. 7** and the dispersion degree of their distribution were significantly higher than those of the other five products, which indicates that the sentiment value of Galaxy_note9 had a large error and a low confidence level. The cloud droplet thickness and dispersion degree for OPPO_R17 in **Fig. 8** were significantly lower than those of the other products, showing that the error of the sentiment value for OPPO_R17 was small, and its confidence level was high.

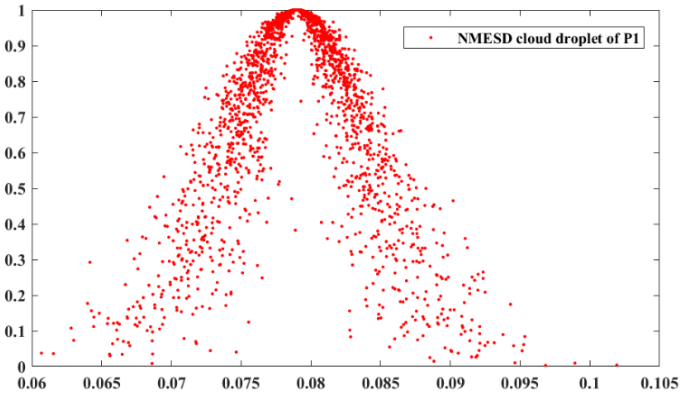

Fig.6. The NMESD cloud droplet distribution of Huawei_mate20 (P1)

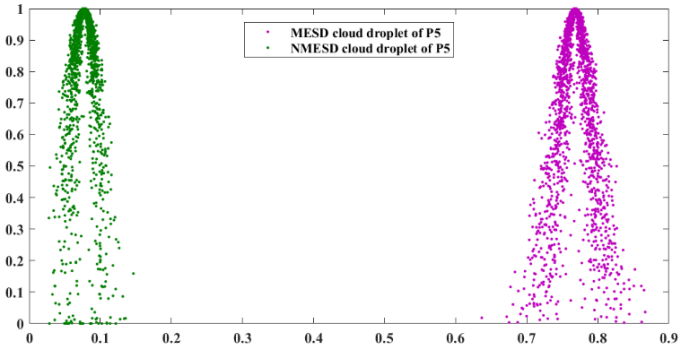

Fig.7. The cloud droplet distribution of Galaxy_note9(P5).

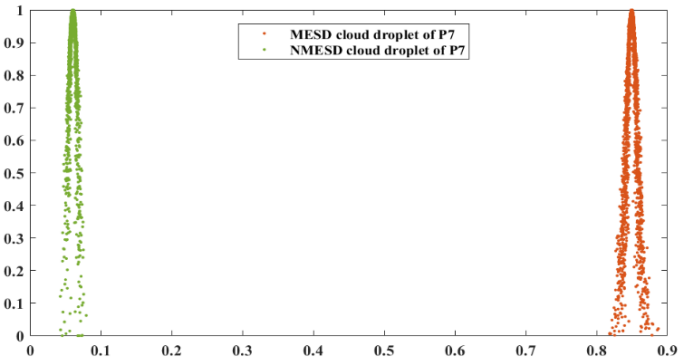

Fig.8. The cloud droplet distribution of OPPO_R17(P7).

Step 7: According to the cloud droplet distribution, we can calculate the comprehensive MESD expectations and NMESD expectations for each product using the MATLAB software, as shown in TABLE VI.

Step 8: Compute the score values G(P*i*) of the seven alternative phones according to Equation (10), as shown in TABLE VII:

G(Huawei_mate20) = 0.5022, G(Iphone_XR) = 0.4781, G(Vivo_Z3) = 0.5572, G(Xiaomi9) = 0.4885, G(Galaxy_note9) = 0.5144, G(Meizu16) = 0.4686, G(OPPO_R17) = 0.5684.

TABLE VI.
THE COMPREHENSIVE MESD EXPECTATIONS AND NMESD EXPECTATIONS.

	$\frac{1}{n}\sum_{i=1}^{n} x_{u_i}$	$\frac{1}{n}\sum_{i=1}^{n} y_{u_i}$	$\frac{1}{n}\sum_{i=1}^{n} x_{v_i}$	$\frac{1}{n}\sum_{i=1}^{n} y_{v_i}$	**G(S*i*)**
Huawei_mate20	0.7911	0.7053	0.07915	0.7045	0.5022
Iphone_XR	0.7758	0.7004	0.09823	0.6642	0.4781
Vivo_Z3	0.8331	0.7243	0.06579	0.7022	0.5572
Xiaomi9	0.7854	0.708	0.0956	0.7071	0.4885
Galaxy_note9	0.7702	0.7401	0.07636	0.728	0.5144
Meizu16	0.7661	0.703	0.1002	0.6986	0.4686
OPPO_R17	0.8495	0.7189	0.06109	0.6929	0.5684

According to the score values, we obtain the following ranking of the alternative phones: OPPO_R17 > Vivo_Z3 > Galaxy_note9 > Huawei_mate20 > Xiaomi9 > Iphone_XR > Meizu16. Therefore, the best choice was OPPO_R17.

In reality, the OPPO_R17 mobile phone is positioned for the mid- to high-end market, which is a consumer group more in line with the Chinese mainland market. The 6 GB + 128 GB version of the OPPO_R17 was listed at 3999 yuan, while the 8 GB + 128 GB market price was 4299 yuan, which is generally affordable for consumers in China. We can infer that, for an ordinary Chinese consumer, the OPPO_R17 was the best choice.

B. *Evaluating the performance of product attributes*

In this section, we will calculate the score of each attribute performance of the product, so as to judge the ranking of each attribute performance and provide guidance for enterprises to identify improvement direction and improve product performance. The method proposed by Liu et al. [26] was used to obtain the score of five attributes for each product. In order to obtain an intuitive ranking of each attribute, we fitted the obtained numerical results to **Fig.9.**

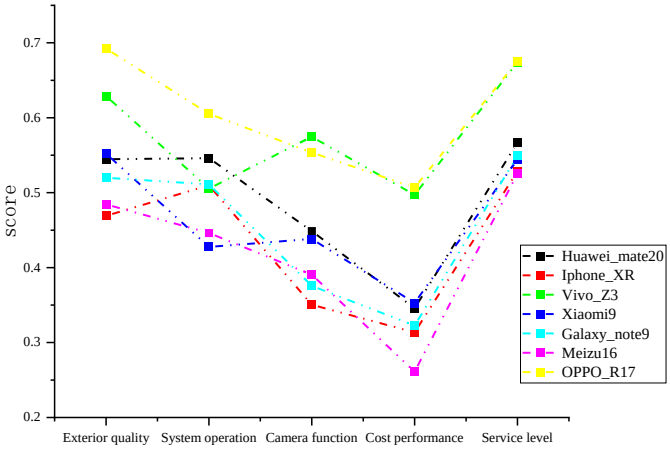

Fig.9. The performance ranking of product attributes

It can be seen from **Fig.9** that OPPO_R17 is the top candidate in Exterior quality, followed by Vivo_Z3 and Xiaomi9, indicating that OPPO_R17 has a high score level in Exterior quality, which leads to its highest popularity among users. In contrast, Meizu16 and Iphone_XR rank in the last two positions, indicating that these two phones have the lowest performance score in Exterior quality. Therefore, the improvement direction of Meizu16 and Iphone_XR products in the future is the Exterior quality, which is conducive to make up for the two products' shortcomings and improve their popularity in the market. For the attribute of System operation, we also find that OPPO_R17 still ranks first, while Meizu16 and Xiaomi9 rank the last two, indicating that the future improvement direction of these two mobile phones should focus on System operation. For the Camera function, Cost performance and Service level, OPPO_R17 and Vivo_Z3 have obvious advantages. Compared with OPPO_R17 and Vivo_Z3, other mobile phones show a significant gap in the scores of these three attributes, especially Meizu16, which has an outstanding low score in Cost performance. As such, OPPO_R17 and Vivo_Z3 should maintain the advantages of Camera function, Cost performance and Service level. Other products should take improving Camera function, reducing cost and enhancing service level as the direction of future improvement.

VI. DISCUSSION

A. Robustness analysis

The parameters K1 and K2 are involved in the proposed method, so it is necessary to investigate the influence of these parameters on the ranking result. We assigned different combinations of random numbers to K1 and K2 and obtained the corresponding ranking results for the mobile phones, as shown in TABLE VII.

TABLE VII
RANKING RESULTS OF ALTERNATIVE PRODUCTS WITH DIFFERENT K-VALUE

Parameters	Mobile phones ranking
K1=1,K2=1	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16
K1=2,K2=1	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16
K1=3,K2=1	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16
K1=1,K2=2	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16
K1=2,K2=2	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16
K1=3,K2=2	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16

According to TABLE VII , when K1 and K2 had a combination of any two values between 1 and 3, the ranking result was always OPPO_R17 > Vivo_Z3 > Galaxy_note9 > Huawei_mate20 > Xiaomi9 > Iphone_XR > Meizu16, and the best choice was always OPPO_R17. We find that even values of K1 and K2 are changed arbitrarily, the result of this example remains robust. Our results suggest that, under a reasonable attribute partition, consumers can choose a reasonable mobile phone without considering too many attributes, which simplifies the decision-making process. The parameters K1 and K2 represent the segmentation of heterogeneous attributes and the clustering of homogeneous attributes. When dealing with actual decision-making problems, we can classify the attributes according to the actual situation and thereby determine the relationships among different quantities of attributes within the same category to obtain the corresponding decision result.

Next, we examine to what extent by altering weighting combinations for attributes will leading to different product recommendations. TABLE VIII Shows the decision result of consumers changes according to the change of attribute weights. Specifically, when consumers consider assigning equal weights to attributes, the result is OPPO_R17> Vivo_Z3> Huawei_mate20> Xiaomi9> Galaxy_note9> Iphone_XR> Meizu16. Even when consumers pay more attention to the attribute of "system operation", OPPO_R17 remains the best choice. However, when consumers only values the last four attributes or three attributes respectively, that is w=(0,0.1,0.2,0.3,0.4) or w=(0,0,0.5,0.2,0.3), the best choice then becomes Vivo_Z3. This highlights the flexibility of our model to allow consumers to set their own subjective weights on attributes to make personalized purchasing decisions by the proposed method.

TABLE VIII
RANKING RESULTS OF ALTERNATIVE PRODUCTS WITH DIFFERENT ATTRIBUTE WEIGHTS.

Attribute weight	Mobile phones ranking
***w*=(0.2,0.2,0.2,0.2,0.2)**	OPPO_R17> Vivo_Z3> Huawei_mate20> Xiaomi9> Galaxy_note9> Iphone_XR> Meizu16
***w*=(0.15,0.4,0.15,0.15,0.15)**	OPPO_R17> Vivo_Z3> Huawei_mate20> Galaxy_note9> Iphone_XR> Xiaomi9> Meizu16
***w*=(0,0.1,0.2,0.3,0.4)**	Vivo_Z3> OPPO_R17> Xiaomi9> Huawei_mate20>Galaxy_note9> Iphone_XR> Meizu16
***w*=(0,0,0.5,0.2,0.3)**	Vivo_Z3> OPPO_R17> Xiaomi9> Huawei_mate20> Galaxy_note9> Meizu16> Iphone_XR

B Comparison analysis

In this section, we compare our proposed method to four existing representative methods, including the methods of Yang *et al*. [36], Mahmood and Ali [43], Liu *et al*. [1], and Liu *et al*. [4]. Note that these four methods were also used to carry out the decision-making problem in our case, and the corresponding ranking results of the seven mobile phones are shown in TABLE IX.

According to TABLE IX, the optimal decision results obtained by the present method were consistent with the results based on the methods by Yang *et al*. [36] and Mahmood and Ali [43] (*i.e*., the OPPO_R17 is the best), demonstrating the validity of our method. However, we

further found that the results obtained by our method differed from those based on the methods by Liu *et al*. [1] and Liu *et al*. [4]. The best choice derived by both of these methods was the Vivo_Z3, while OPPO_R17 was the second-best choice.

In light of the different ranking results based on different methods, we analysed the reasons for the above-mentioned phenomena by considering the differences in the models themselves. Although the optimal results based on our method were consistent with those based on the methods by Yang *et al*. [36] and Mahmood and Ali [43], the overall ranking was obviously different. For example, Galaxy_note9 ranked sixth in the sorting results using the methods by Yang *et al*. [36] and Mahmood and Ali [43], but ranked third in the sorting results using the proposed method. The different rankings might because neither Yang *et al*. [36] nor Mahmood and Ali [43] have investigated the confidence level $z_{\theta/2}$ of the sentiment value of attributes. Recall that different numbers of sentiments have a certain impact on the calculation of sentiment value. In our method, the confidence level of attribute information was fully considered by introducing the cloud model; the error and excess error characteristics of the attribute sentiment value were calculated based on the binomial distribution, which were then embedded into our method. Meanwhile, the concept of q-ROFC was defined to calculate the influence of the error distribution characteristics of the sentiment value on product rankings. Moreover, Yang *et al*. [36] and Mahmood and Ali [43] did not utilise the heterogeneous characteristics of attributes and simply assumed that all product attributes were homogeneous; that is, they did not investigate the different impacts of different types of attributes on information aggregation. In our proposed method, we take functional characteristics into one group (e.g., exterior quality; system operation, and camera function), while non-functional aspects of mobile phones have been classified into another group (e.g., cost performance, service level). Therefore, we could analyse the influence of attributes in each of the groups on the decision results, and avoiding an unfair ranking caused by interaction relationships between different types of attributes.

In addition, when the proposed method's sorting results were compared to those of Liu *et al*. [1] and Liu *et al*. [4], there were significant differences between the optimal results and the full order. This is because Liu *et al*. [1] and Liu *et al*. [4] did not examine the interactive influence process of attribute sentiment values across platforms on consumer purchasing decisions; instead, they simply added the attribute sentiment values across platforms and then aggregated the attribute information using the traditional linear weighted average concept to obtain a sorting result. In contrast, we developed cross-combinations of sentiment values from the same attributes on different platforms to generate multiple interactive decision matrices. The interaction operator was then introduced, and a new q-ROFCIWPMSM operator was proposed to describe the interactive influence characteristics of attribute sentiment information from different platforms, which fully reflects the interactive influence process of multi-platform reviews on consumer decision-making in the actual decision-making process. Furthermore, Liu *et al*. [1] and Liu *et al*. [4] did not investigate the heterogeneity of attributes and the relationships between attributes in a homogenous attribute group, but instead treated all attributes as homogeneous and as a single group, which reduced the influence of some important attributes and/or increased the influence of non-important attributes on decision-making outcomes. In contrast, heterogeneous attributes were segmented in this paper based on the idea of attribute segmentation, and the MSM operator was introduced to investigate the interactive relationships between any number of attributes in each group.

TABLE IX
COMPARISON ANALYSIS WITH DIFFERENT METHODS.

Method	Mobile phone ranking
Yang *et al.* [36]	OPPO_R17> Vivo_Z3> Huawei_mate20> Xiaomi9 > Iphone_XR>Galaxy_note9> Meizu16
Mahmood and Ali [43]	OPPO_R17> Vivo_Z3> Huawei_mate20> Xiaomi9 > Iphone_XR>Galaxy_note9> Meizu16
Liu *et al.* [1]	Vivo_Z3>OPPO_R17>Huawei_mate20 >Xiaomi9>Galaxy_note9> Iphone_XR> Meizu16
Liu *et al.* [4]	Vivo_Z3>OPPO_R17>Huawei_mate20 >Xiaomi9>Galaxy_note9> Iphone_XR> Meizu16
The proposed method	OPPO_R17> Vivo_Z3> Galaxy_note9> Huawei_mate20> Xiaomi9> Iphone_XR> Meizu16

C. Decision results under a single platform

In addition, we also compute the decision-making results under a single e-commerce platform, as shown in TABLE X. When consumers only refer to the customer reviews on the JD platform, the product ranking result is OPPO_R17 > Xiaomi9 > Huawei_mate20 > Iphone_XR > Vivo_Z3 > Galaxy_note9 > Meizu16. If consumers just refer to customer reviews on the Tmall platform, the product ranking result becomes Iphone_XR> OPPO_R17 > Galaxy_note9 > Meizu16 > Xiaomi9 > Huawei_mate20 > Vivo 23. It shows that the decision results vary significantly based on different single platforms and leading to impartial recommendations that prevent/delay their purchasing decisions.

TABLE X
PRODUCT RANKING RESULTS UNDER A SINGLE PLATFORM AND MULTI-PLATFORMS

Platform	Ranking results
JD	OPPO_R17>Xiaomi9>Huawei_mate20>Iphone_XR>Vivo_Z3>Galaxy_note9>Meizu16
Tmall	Iphone_XR>OPPO_R17>Galaxy_note9>Meizu16>Xiaomi9>Huawei_mate20>Vivo 23
JD*Tmall	OPPO_R17>Vivo_Z3>Galaxy_note9>Huawei_mate20>Xiaomi9 > Iphone_XR > Meizu16.

In reality, many consumers will compare the product reviews from multiple platforms before making the purchase decisions (any references?). Our proposed method allows one to make an informed decision while considering the influence of multi-platform interaction. Based on our model, we recommend OPPO_R17> Vivo_Z3> Galaxy_note9>

Huawei_mate20> Xiaomi9 > Iphone_XR> Meizu16, which are different from the decision results under former two situations. This manifests that the product ranking is biased considering a platform alone. Due to differences between platforms, product attribute reviews will vary greatly in quantity and quality, which will lead to different rankings of products on different single platform. The proposed method comprehensively examines the impact of review sentiment interaction of different platforms on decision results, which can avoid the decision bias generated by a single platform.

VII. CONCLUSIONS

Online reviews have become an important basis for consumer purchasing decisions and product performance improvement. Therefore, it is necessary to establish an effective product decision model based on multi-platform reviews. Many previous works have focused on product purchasing decision-making methods influenced by online reviews. Online product purchasing decision methods that combine fuzzy set theory with review mining, in particular, have grown in importance. However, existing methods simply integrate multi-platform reviews to build a comprehensive decision matrix based on a linear sum, develop simple representations using IFSs, and ultimately use the operational rules of IFSs to obtain the rankings of products. These methods ignore the interactive impact of multi-platform reviews on consumers, as well as the error characteristics and confidence levels of sentiment calculation, both of which inevitably affect the final product decision-making results. As a result, in this study, we proposed an online product ranking and performance evaluating method combining BiLSTM-CRF-based attribute mining and the q-ROFCIWPMSM operator to overcome the aforementioned limitations. From the perspective of consumers and merchants, the practical implications are as follows:

(1) Consumers can obtain effective support for making online purchase decisions based on the proposed algorithm framework in this study. Consumers can use this framework to effectively deal with the contradictory reviews from multiple platforms and obtain the corresponding product ranking results based on the interactive decision matrix and cloud model. At the same time, it can provide consumers with personalised purchase decision results based on product ranking across various attributes.

(2) Based on the evaluation results of product attribute performance, merchants can optimise products and improve product competitiveness. Our method can synthesise word-of-mouth/ user feedback from various platforms and detect the positive and negative attributes of various aspects of products. As a result, merchants can improve and optimise the product attributes with poor word-of-mouth/ user feedback, thereby improving the overall quality of the product and market competitiveness.

Future research could focus on the perspective of online multi-source heterogeneous data and provide support for product decisions from various market players via the fusion of multi-source online data. At present, the development forms of e-commerce platforms are diverse, with e-commerce platforms based on the social model generating multi-source heterogeneous data, such as images and textual data, and e-commerce platforms based on the short video content model generating video and voice data. The large amount of heterogeneous data associated with products produced by various types of e-commerce platforms conceal more important information values. In addition, aspect of fineness sentiment based on new fuzzy set model and its support for product decision should be considered. Mining this type of multi-source heterogeneous data and fineness sentiment of product reviews not only provides decision-making support for consumer purchases, but also serves as a decision-making reference for product sales strategies for merchants, operational optimisation for platforms, product design for manufacturers, and express business improvement for logistics providers.

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