mathematics

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Product Selection Considering Multiple Consumers' Expectations and Online Reviews: A Method Based on Intuitionistic Fuzzy Soft Sets and TODIM

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Abstract: Large amounts of online reviews from e-commerce sites and social media platforms can help potential consumers to better understand products and play an important part in assisting potential consumers in making purchase decisions. Moreover, while multiple consumers purchase the same product, the index parameters of the product that are of concern among them are usually different, i.e., they have different expectations for the product. Therefore, the question of how to effectively analyze online product reviews and consider multiple consumers' expectations to select products is an important issue that needs to be addressed. The objective of this study is to propose a product selection method based on intuitionistic fuzzy soft sets and TODIM. Firstly, the online reviews are extracted by the web crawler and are pretreated. Next, the sentiment orientations of each online review concerning product index parameters are recognized using the dictionary-based sentiment analysis algorithm. Then, the evaluation values of sentiment orientations for product index parameters are firstly expressed by intuitionistic fuzzy numbers and are then transformed into intuitionistic fuzzy soft sets. Further, the alternative product set is obtained according to the *uni-int* decision function and multiple consumers' expectations, and we then rank the alternative products using the TODIM method. Finally, a case study is provided to illustrate the validity and feasibility of the proposed method.

Keywords: product selection; online reviews; multiple consumers' expectations; intuitionistic fuzzy soft sets; sentiment analysis; TODIM

MSC: 90B50

Citation: Cao, P.; Zheng, J.; Li, M. Product Selection Considering Multiple Consumers' Expectations and Online Reviews: A Method Based on Intuitionistic Fuzzy Soft Sets and TODIM. *Mathematics* **2023**, *11*, 3767. https://doi.org/10.3390/math11173767

Academic Editor: Hsien-Chung Wu

Received: 6 August 2023
Revised: 27 August 2023
Accepted: 30 August 2023
Published: 1 September 2023

1. Introduction

With the rapid development of e-commerce and social media, more and more consumers post online reviews about purchased products through e-commerce sites and social media platforms [1,2]. Online reviews refer to the consumer's comments on a particular product published on the corresponding review website after purchasing it. As an important part of e-commerce product selection [3], online reviews reflect the experiences, evaluations, and opinions of customers who have purchased and used products. The content of online reviews usually includes two types: the form of star ratings and open-ended comments written by customers about the product. For consumers, comments are more valuable than ratings [4]. Online reviews are a direct link between products and consumers, providing consumer-derived product information and providing advice to other consumers through electronic word-of-mouth [5]. Compared to the product information provided by sellers, the online reviews shared by consumers can more objectively reflect the products [6–8]. These online reviews have become an important information resource for potential consumers to understand the quality of products and make purchase decisions [9–13]. They have greater advantages over other traditional information media in enhancing consumer trust in businesses and increasing consumer willingness to purchase. However, the quantity of online reviews is huge and the online reviews have diverse content [14–16]. It is impossible for consumers to read and analyze all the online reviews about the products that they are interested in and make comprehensive evaluations directly. Therefore, the question of how to efficiently make use of online reviews to rank products and then provide support for consumers to make purchase decisions is an important research topic.

Studies on product selection based on online reviews have attracted the attention of some scholars. Li, Wu, and Luo [17] proposed a product evaluation model, in which the product was evaluated comprehensively with social network analysis theory. Kang and Park [18] extracted attributes from online reviews using text mining, performed sentiment analysis, and measured customer satisfaction via the VIKOR approach; then, a ranking of mobile services was obtained. Chen et al. [14] extracted attributes from online reviews via the topic modeling approach, calculated the weights of attributes via the WVAP approach, and then ranked the products via the TOPSIS approach, thus visualizing the market structure. Najmi et al. [19] proposed a product ranking system in which the ranking results were determined by integrating sentiment analysis, product analysis, brand rankings of products, and the usefulness analysis of reviews. Yang et al. [20] proposed a ranking system for multiple products by integrating rich and heterogeneous information, including numeric ratings, text descriptions, and comparative words. Liu et al. [21] proposed an online ranking method based on the sentiment analysis technique and the intuitionistic fuzzy set theory, and the PROMETHEE-II method was used to rank the alternative products. Fan et al. [22] studied the ranking of candidate products based on online multi-attribute product ratings, and the 3σ criterion was used to eliminate the anomalous ratings. In the studies of Bi, Liu, and Fan [6], the limited accuracy rates of the sentiment analysis results were considered, and interval type-2 fuzzy numbers were used to represent the sentiment analysis results from online reviews; then, a method for product ranking was proposed. In the studies of Liang and Wang [23], the randomness and fuzziness of online reviews and the interrelationships among product features were considered, and an integrated decision support model was presented. Liu and Teng [1] provided an extended probabilistic linguistic TODIM method to rank products based on online product reviews, which preserved the advantages of the classical TODIM method and probabilistic linguistic term sets. Zhang, Li, and Wu [24] proposed a product ranking method through online reviews, which improved the classical TODIM method and comprehensively used the intuitionistic fuzzy set theory, sentiment analysis, and multi-attribute decision making. Zhang, Tian, Fan, and Li [25] proposed a product ranking method based on online reviews, which mainly included three stages, i.e., generating a list of related alternative products based on specific filtering conditions, collecting and processing online reviews of alternative products, and measuring customer satisfaction. Wu and Ye [26] proposed a basket-sensitive personalized ranking method to solve the paired ranking problem among users and products. The method utilizes joint paired ranking to discover mutual correlations among users and products, alleviating the inherent flaws in existing paired methods. Nie et al. [27] constructed an online textual review-driven hotel selection model, in which a semantic mapping function and the method of building a domain dictionary were proposed, and a fusion method based on evidence theory was proposed to ensure the reliability of the results. Li et al. [28] proposed product selection methods for single consumers and group consumers, in which the product attributes are divided into two categories, i.e., demand attributes and word-of-mouth attributes. Teng, Liu, and Witold [29] constructed a method based on probabilistic linguistic term sets. The performance of this method was illustrated by the case of selecting smart phones through online ratings. Luo et al. [30] established a multi-dimensional evaluation index system based on online reviews of tourist attractions and processed the results of sentiment orientation based on probabilistic linguistic term sets, so as to rank the final evaluations of tourist attractions. Dahooie et al. [31] proposed an integrated framework that combined sentiment analysis, intuitionistic fuzzy sets, and multi-criteria decision-making technologies to solve the product ranking problem based on online customer reviews. Zhang, Guo, et al. [13] presented a product selection model based on sentiment analysis and the intuitionistic fuzzy TODIM method. Zhang, Liang, and Xu [32] presented a new hotel evaluation model, which integrated both ratings and comments from multiple websites, and a weighted averaging linear assignment model was used to rank the hotels. Zhao et al. [33] proposed a multi-criteria decision-making method incorporating personalized heuristic judgments in prospect theory to solve a personalized product selection problem with review sentiments under probabilistic linguistic circumstances. Qin, Xu, and Zheng [34] established an axiomatic framework for the fuzzy entropy and overall entropy of T2FSs and proposed a decision method based on type-2 fuzzy entropy, which was applied to the selection of cold medicine through online reviews. Yin, Wang, and Shafiee [35] proposed a product ranking method based on bidirectional encoder representation considering the mass assignment of features. In this method, a transformer was used to identify the sentiment orientation and product features, and the q-rung orthopair fuzzy numbers were aggregated by the q-rung orthopair fuzzy generalized weighted Heronian mean operator to rank the products. Qin and Zeng [36] proposed a comprehensive method for product ranking through online reviews. In this method, naive Bayes, logistic regression, and support vector machine were used for the sentiment analysis of online reviews, and the stochastic multi-criteria acceptability analysis PROMETHEE method was used to obtain the final product ranking results. Eshkevari et al. [37] proposed an end-to-end ranking method that ranked the quality of hotel services, facilities, and amenities based on customer reviews. This method integrated mechanisms such as text processing, sentiment analysis, and multi-criteria decision-making technology. Tayal et al. [38] proposed a method for the personalized ranking of products based on multiple aspects. This method combined different customer preferences by mapping them to plithogenic degrees of contradictions and modeling linguistic uncertainties in online reviews to create a personalized ranking of products using splitting aggregation. Li, Chen, and Zhang [39] developed a product ranking method based on multiple classifiers and interval-valued intuitionistic fuzzy TOPSIS, which can help consumers to choose products that match their preferences based on online reviews.

The existing studies have made significant contributions to product selection based on online reviews. However, there are still some limitations, which are expressed as follows.

(1) Most existing studies mainly focus on solving the product selection problems that arise when the consumers do not provide their expectations of products. In these studies [21,22,40,41], the performance values of products concerning attributes are determined by analyzing online reviews, and the performance values of each product attribute are aggregated to obtain the ranking of alternative products. Consumers' expectations or preferences for products are rarely considered in existing studies. In fact, consumers usually provide their index parameters of concern regarding the product based on their own subjective preferences and provide their expectations concerning these index parameters. For example, "high cost-effectiveness" is the index parameter highlighted by a consumer when he/she buys a digital camera, so he/she will view the online reviews about the "high cost-effectiveness" of the camera on the relevant sites. He/she expects the level of the camera to meet the index parameter "high cost-effectiveness" at no less than 0.8, and for the camera not to meet the index parameter "high cost-effectiveness", its value would be no more than 0.1. Thus, this paper conducts research on product selection whereby consumers provide their expectations of products. By considering multiple consumers' expectations and online reviews, products are screened, and alternative products that meet consumers' expectations are obtained. Then, alternative products are ranked to effectively help multiple consumers (a group) to select suitable products based on the performance of alternative products.

(2) Neutral sentiment orientation is rarely considered in existing studies [14,19,42,43], which can result in the loss of information. In fact, there are a large number of reviews about neutral sentiment orientations on the relevant sites, which means that the consumers' opinions are uncertain. However, the uncertainty information is also very important, as it can provide more information for potential consumers and help them to make reasonable purchase decisions.
(3) Although existing studies provide product selection methods for one single consumer, they do not focus on the topic of multiple consumers (a group) purchasing the same product [21,22,41], nor do they consider the different index parameters and expectations that consumers are concerned about. However, group buying is also common in reality. For this situation, a product selection method for multiple consumers needs to be developed, which has wider application scope.
(4) Existing studies usually assume that consumers are completely rational, while ignoring consumers' psychological behaviors when they select products and make purchase decisions [21,41,44]. In fact, consumers usually display bounded rationality when they select products and make purchase decisions.

Therefore, the development of a new method for product selection is necessary; this method can help multiple consumers (a group) to select the right product based on the index parameters and expectations expressed by multiple consumers. In order to avoid the information loss of online reviews, three sentiment orientations of consumers are considered, including positive sentiments, neutral sentiments, and negative sentiments. Because the intuitionistic fuzzy soft set includes membership, non-membership, and hesitation simultaneously, it is an effective tool to express sentiment orientations and intensities in online reviews, and it can be applied to solve the product selection problem in the situation that multiple consumers focus on different index parameters. Thus, the sentiment orientations of consumers can be transformed into intuitionistic fuzzy soft sets. In addition, consumers' psychological behaviors should be considered, including reference dependence and loss aversion. This is the motivation of this study.

The aim of this study is to provide a product selection method based on intuitionistic fuzzy soft sets and TODIM, and multiple consumers' expectations and online reviews are considered in this method. Firstly, the online reviews are extracted by the web crawler and are pretreated. Next, the sentiment orientations of each online review concerning the product index parameters are recognized using the dictionary-based sentiment analysis algorithm. Then, the evaluation values of sentiment orientations for product index parameters are firstly expressed by intuitionistic fuzzy numbers and are then transformed into intuitionistic fuzzy soft sets. Further, the alternative product set is obtained according to multiple consumers' expected products. Finally, the overall dominant degrees of alternative products are calculated using the TODIM method, and then the ranking of alternative products is obtained.

The remainder of the paper is organized as follows. Section 2 provides preliminaries that contain some basic concepts used in this study. Section 3 describes the problem of product selection considering multiple consumers' expectations and online reviews. Section 4 proposes a method for product selection considering multiple consumers' expectations and online reviews. Section 5 shows the application of the proposed method to a digital camera selection problem. The contributions and limitations of this study are concluded in Section 6.

2. Preliminaries

In this section, some basic concepts, such as the soft set, fuzzy soft set, intuitionistic fuzzy set, and intuitionistic fuzzy soft set, are introduced.

Molodtsov [45] proposed the concept of a soft set. A soft set is a parameterized family of subsets of a universal set, and it is a mathematical structure that extends the idea of a traditional set. In a soft set, elements can have a degree of membership or association with the set, which allows for a more flexible representation of uncertainty or vagueness.

Definition 1 ([45])**.** *Let U be an initial universe, E be the set of parameters, $P(U)$ be the power set of U, and $A \subseteq E$. If (F, A) be the set of ordered pairs of U, and $F : A \to P(U)$ is a map; then, (F, A) is called a soft set of U.*

Çağman and Enginoğlu [46] proposed a *uni-int* decision-making method based on soft sets by defining the $\wedge$-product operation rule of soft sets. This method can be used to synthesize the evaluation information of the different indicator sets provided by two parties. In the *uni-int* decision method, the $\wedge$-product operation is first performed on two given soft sets, and then the *uni-int* operator is used to find the *uni-int* decision set that contains the optimal decision scheme. The $\wedge$-product operation of soft sets, *uni-int* operator, and *uni-int* decision function are as follows.

Definition 2 ((the $\wedge$-product operation of soft sets) [46])**.** *Let $S(U)$ be the set of all soft sets over U, and $(F, A), (F, B) \in S(U)$. If the approximate function of a new soft set $(F, A) \wedge (F, B)$ is $f_{A \wedge B} : E \times E \to P(U)$, and $f_{A \wedge B}(x, y) = f_A(x) \cap f_B(y)$, then $(F, A) \wedge (F, B)$ is called the product operation of (F, A) and (F, B).*

Let $\wedge$(U) be the set of soft sets obtained by the product operations of any two soft sets over U; then, the definition of the *uni-int* operator based on the product operation of soft sets and the decision function can be expressed as follows.

Definition 3 ((uni-int operator) [46])**.** *Let $(F, A) \wedge (F, B) \in \wedge(U)$; the uni-int operators based on the product operation of (F, A) and (F, B) are the $uni_x int_y$ operator and $uni_y int_x$ operator, which are expressed as follows:*

$$uni_x int_y\!: \wedge(U) \to P(U),\ uni_x int_y((F, A) \wedge (F, B)) = \bigcup_{y \in A}\Big(\bigcap_{x \in B}(f_{A \wedge B}(x, y))\Big),$$
$$uni_y int_x\!: \wedge(U) \to P(U),\ uni_y int_x((F, A) \wedge (F, B)) = \bigcup_{y \in B}\Big(\bigcap_{x \in A}(f_{A \wedge B}(x, y))\Big).$$

Definition 4 ((*uni-int* decision function) [46])**.** *Let $(F, A) \wedge (F, B) \in \wedge(U)$; the uni-int decision function based on the product operation of (F, A) and (F, B) is $uni - int((F, A) \wedge (F, B))$, which is expressed as follows:*

$$\text{uni-int}\!: \wedge(U) \to P(U),$$
$$uni - int((F, A) \wedge (F, B)) = uni_x int_y((F, A) \wedge (F, B)) \cup uni_y int_x((F, A) \wedge (F, B)).$$

Maji, Roy, and Biswas [47] introduced the concept of a fuzzy soft set by combining a soft set with a fuzzy set. A fuzzy soft set can be seen as a parameterized family of fuzzy sets of a universe, which is an extension of fuzzy sets. It is an object expression model based on parameters and represented by fuzzy information. It is no longer limited to the simple description of object parameters by a precise soft set but rather expresses the degree of parameter membership in a more flexible fuzzy form, which can be widely applied to uncertain situations in various fields.

Definition 5 ([47])**.** *Let U be an initial universe, E be the set of parameters, $FS(U)$ be all the fuzzy sets over U, and $A \subseteq E$. If $F : A \to FS(U)$ is a map, then (F, A) is called a fuzzy soft set over U.*

The intuitionistic fuzzy set was proposed by Atanassov [48], which is associated with every element in the universe and not only has membership functions but also has non-membership functions. It provides more options to describe the attributes of objects and has stronger expressive power in handling uncertain information.

Definition 6 ([48])**.** *Let X be a nonempty universe; then, $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\}$ is called an intuitionistic fuzzy set over X, in which $\mu_A(x)$ is the membership function of element x in X on A, $\nu_A(x)$ is the non-membership function of element x in X on A, and $\mu_A(x) : X \to [0, 1]$,*

$\nu_A(x) : X \to [0,1]$, and $0 \le \mu_A(x) + \nu_A(x) \le 1$ for $\forall x \in X$. $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is called the hesitation function of element x on A.

Maji, Biswas, and Roy [49] proposed the concept of an intuitionistic fuzzy soft set by combining an intuitionistic fuzzy set and a soft set. An intuitionistic fuzzy soft set can be regarded as a parameterized family of intuitionistic fuzzy sets of a universe. Due to the unconstrained parameter setting in a soft set, it is more widely and flexibly applied than an intuitionistic fuzzy set and can provide richer descriptions of uncertain information, making the decision-making process easier and more accurate.

Definition 7 ([49])**.** *Let U be an initial universe, E be the set of parameters, $IFS(U)$ be the set of all intuitionistic fuzzy sets of U, and $A \subseteq E$. If $F : A \to IFS(U)$ is a map, then (F, A) is called an intuitionistic fuzzy soft set of U. For $\forall e \in A$, $F(e) = \left\{ \left\langle x, \mu_{F(e)}(x), \nu_{F(e)}(x) \right\rangle \middle| x \in U \right\}$, in which $\mu_{F(e)}(x)$ is the membership function of x on intuitionistic fuzzy soft set $F(e)$, $\nu_{F(e)}(x)$ is the non-membership function of x on intuitionistic fuzzy soft set $F(e)$, and $\mu_{F(e)}(x) : U \to [0,1]$, $\nu_{F(e)}(x) : U \to [0,1]$, and $0 \le \mu_{F(e)}(x) + \nu_{F(e)}(x) \le 1$ for $\forall x \in U$. $\pi_{F(e)}(x) = 1 - \mu_{F(e)}(x) - \nu_{F(e)}(x)$ is called the hesitation function of x on $F(e)$.*

3. Problem Description and the Resolution Procedure

Taking the selection of digital cameras as an example, the product selection problem is shown in Figure 1. Consider a group that wants to purchase a digital camera in bulk. This group is made up of interested, organized consumers who have similar usage needs, such as a company department. Several digital cameras are determined through preliminary investigation. However, due to differences in knowledge and experience, the consumers in the group have different preferences (product index parameters considered and expectations of index parameters) for digital cameras, causing the group to waver among several digital cameras. In order to select a digital camera that satisfies all consumers in the group as much as possible, it is necessary to comprehensively consider the personalized preferences of the consumers. To support the purchase decision of this group, a large number of online reviews of related products are crawled from relevant websites, digital cameras are screened based on consumer preferences, and the screened digital cameras are ranked.

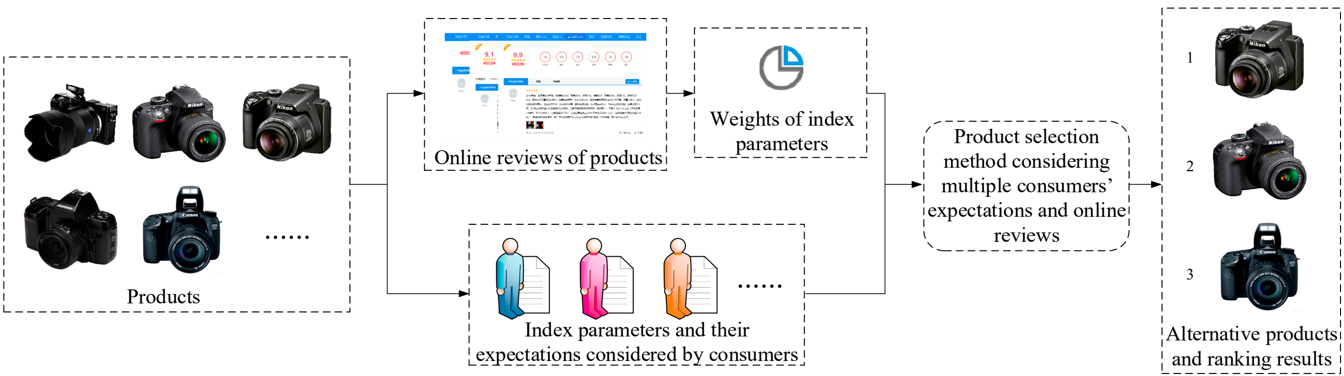

Figure 1. The product selection problem considering multiple consumers' expectations and online reviews.

To facilitate our description, the following notations are used to denote the sets and variables in this problem.

- $U = \{u_1, u_2, \ldots, u_m\}$: the set of products considered by consumers, where u_i denotes the ith product, $i \in I$, $I = \{1, 2, \ldots, m\}$.
- $D = \{D_1, D_2, \ldots, D_p\}$: the set of p consumers, where D_k denotes the kth consumer, $k = 1, 2, \ldots, p$.

- $E = \{e_1, e_2, \ldots, e_n\}$: the set of n index parameters, where e_j denotes the jth index parameter, $j = 1, 2, \ldots, n$.
- $E_k = \{e_1^k, e_2^k, \ldots, e_{L_k}^k\}$: the set of index parameters considered by consumer D_k, where e_l^k denotes the lth index parameter considered by consumer D_k, $l = 1, 2, \ldots, L_k$, $E_k \subseteq E$, $L_k \leq n$.
- $AL_l^k(s_l^k, t_l^k)$: the expectation about index parameter e_l^k given by consumer D_k, $s_l^k, t_l^k \in [0,1]$ and $0 \leq s_l^k + t_l^k \leq 1$. s_l^k and t_l^k represent the acceptable levels of membership and non-membership given by the consumer about a product that conforms to the index parameter, i.e., the extent to which the product conforms to the index parameter and the extent to which the product does not conform to the index parameter. It means that the consumer expects the extent to which the product conforms to the index parameter to be not less than s_l^k, and the extent to which the product does not conform to the index parameter to be no higher than t_l^k.
- $W = (w_1, w_2, \ldots, w_n)$: the weight vector of the index parameters, where w_j denotes the weight of e_j, and $0 \leq w_j \leq 1$, $\sum_{j=1}^{n} w_j = 1$.
- $R_i = \{R_{i1}, R_{i2}, \ldots, R_{iq_i}\}$: the set of online reviews of product u_i, where R_{iv} denotes the vth online review, $i \in I$, $v = 1, 2, \cdots, q_i$.

Based on the above statement, the product selection problem considering multiple consumers' expectations and online reviews to be solved in this paper is how to help consumers to select the right product by screening products $u_1, u_2, \ldots, u_m$ and ranking the screened products based on the index parameter set E_k considered by consumer D_k, the expectations $AL_l^k(s_l^k, t_l^k)$ of index parameter e_l^k, online reviews R_i, and the weights W of the index parameters.

To address the above problem, a resolution process is outlined in Figure 2. As can be seen from Figure 2, the resolution process can be divided into two parts, i.e., (1) product screening considering consumer expectations, and (2) product ranking based on TODIM. In the first part, the web crawler software is used to obtain online reviews of products from relevant websites, and the Jieba toolkit is used for preprocessing. Secondly, based on the HowNet sentiment dictionary and online reviews, a sentiment dictionary for the products is established. Next, the sentiment orientations of each online review toward the product index parameters are recognized using the dictionary-based sentiment analysis algorithm. Furthermore, based on the theory of intuitionistic fuzzy soft sets, the sentiment orientations are transformed into intuitionistic fuzzy soft sets. On this basis, a set of alternative products that meet the consumer expectations is selected based on the *uni-int* decision function and the expectations of multiple consumers. In the second part, according to the score function values, the scores of alternative products concerning the index parameters are compared in pairs, and the gain–loss matrix can be built. Then, the weights of the index parameters and relative weights are obtained based on intuitionistic fuzzy soft set entropy. Furthermore, the overall dominance degree of each alternative product over other alternative products is calculated and a ranking of the alternative products can be determined using the TODIM method.

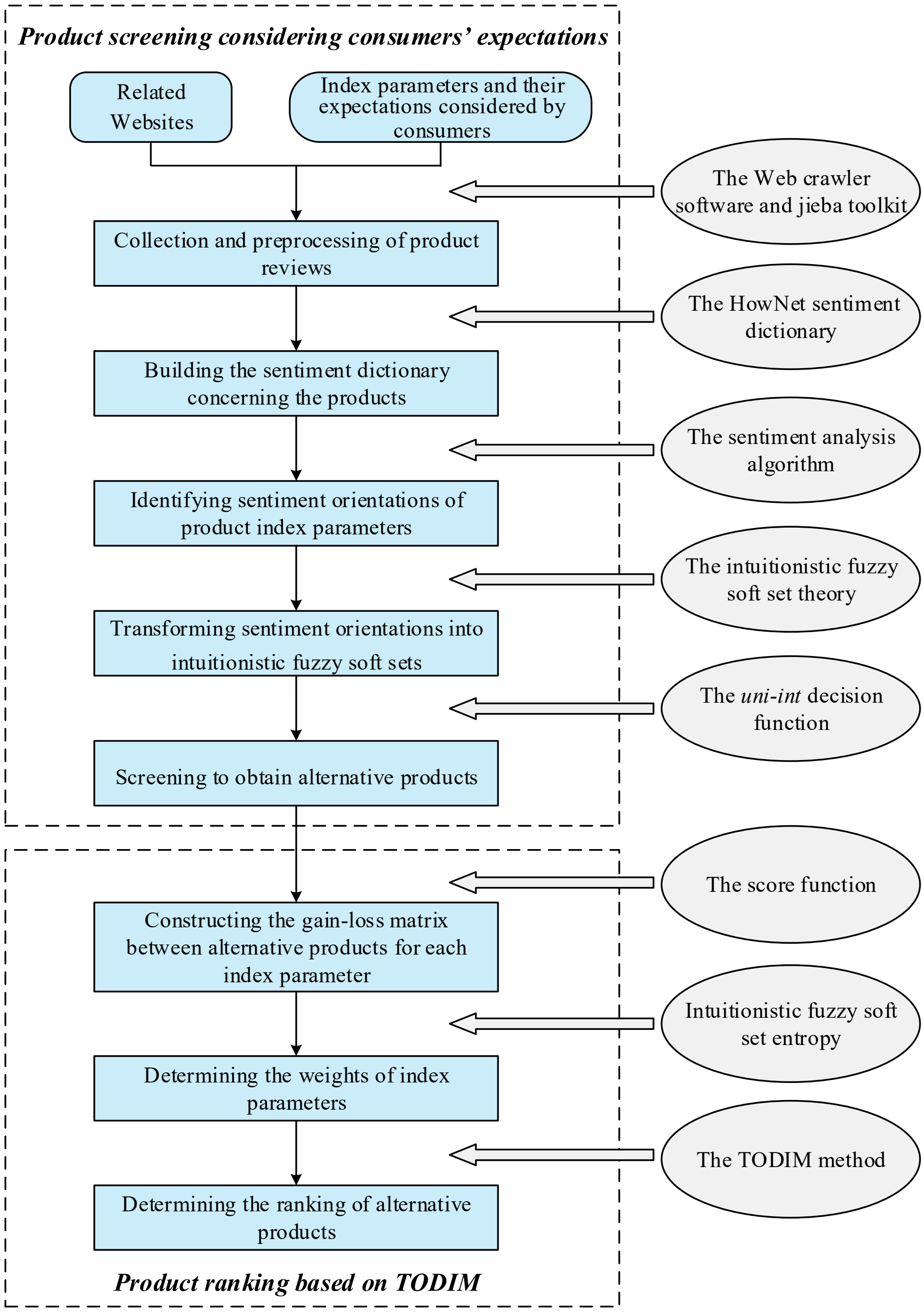

Figure 2. The resolution process for the product selection problem considering multiple consumers' expectations and online reviews.

4. Methodology

Following the resolution process in Section 3, this section proposes a methodology for product selection considering multiple consumers' expectations and online reviews, which is described in detail in the following sections.

4.1. Sentiment Analysis Based on Online Reviews of Products

The extraction and pretreatment of online reviews are the fundamental tasks in the sentiment analysis of online reviews. According to the product set $U = \{u_1, u_2, \ldots, u_m\}$ considered by the consumers, the online reviews that conform to the rules (such as word count and post time of reviews) are extracted by the web crawler from the relevant sites, and then the online reviews $R_i = \left\{R_{i1}, R_{i2}, \ldots, R_{iq_i}\right\}$ of product u_i can be obtained, $i \in I$. Then, we pretreat the online reviews obtained, including word segmentation, part-of-speech tagging, and stop word removal. The process can be expressed as follows. (1) Perform the word segmentation of online reviews and conduct part-of-speech tagging using the word segmentation tool Jieba of Python. The online reviews in the form of sentences are divided into several words, and the part-of-speech is tagged after each word. (2) Remove the stop words. Stop words are words that frequently appear but are meaningless; in order to improve the efficiency of sentiment analysis, in this study, the online reviews after word segmentation and part-of-speech tagging are compared with stop words in a Chinese stop word list, and the words that appear in the stop word list are removed and the punctuation marks are left. After the pretreatment of the online reviews, the word set $ED_{iv} = \left\{ED_{iv}^1, ED_{iv}^2, \ldots, ED_{iv}^{q_{iv}}\right\}$ of the vth online review of product u_i can be obtained, where ED_{iv}^{σ} denotes the σth word in ED_{iv}, q_{iv} denotes the total number of words in ED_{iv}, $i \in I$, $v = 1, 2, \cdots, q_i$, $\sigma = 1, 2, \cdots, q_{iv}$.

Usually, each online review contains review information of multiple index parameters. In order to identify the sentiments of different index parameters in each online review, the review information of different index parameters in each online review needs to be identified. Because the index parameters considered by consumers usually consist of nouns and adjectives or consist of verbs and adjectives, for the convenience of identifying the reviews of different index parameters, it is necessary to extract nouns or verbs from all index parameters. Let c_j denote the nouns or verbs corresponding to e_j; then, the words in ED_{iv} are compared with c_j, and the adjectives, nouns, verbs, and adverbs are extracted from the reviews between two adjacent punctuation marks in ED_{iv} including c_j [21,50,51]. Then, the review information $ED_{iv}^j = \{ED_{iv1}^j, ED_{iv2}^j, \ldots, ED_{ivq_{iv}^j}^j\}$ corresponding to e_j in the vth online review of product u_i can be obtained, where ED_{ivu}^j denotes the uth word in ED_{iv}^j, q_{iv}^j denotes the total number of words in ED_{iv}^j, $i \in I$, $v = 1, 2, \cdots, q_i$, $j = 1, 2, \ldots, n$.

As the sentiment words of different products may be different, it is necessary to build a dictionary related to the products to improve the accuracy of sentiment analysis. Let $ED' = \left\{ED_1, ED_2, \ldots, ED_{q'}\right\}$ denote the set of sentiment words for product reviews, where ED_R denotes the Rth opinion word in ED', $R = 1, 2, \ldots, q'$.

$$ED' = ED_{11}^1 \cup ED_{12}^1 \cup \cdots \cup ED_{iv}^j \cup \cdots \cup ED_{mq_m}^n \tag{1}$$

The dictionary for the products can be built according to the HowNet sentiment dictionary and the set of sentiment words ED'. Specifically, let ED_{HowNet}^+ and ED_{HowNet}^- denote the positive and negative sentiment dictionary in HowNet; then, the positive sentiment dictionary ED^+ and negative sentiment dictionary ED^- related to the products are built according to ED', ED_{HowNet}^+, and ED_{HowNet}^-.

$$ED^+ = ED_{HowNet}^+ \cap ED' \tag{2}$$

$$ED^- = ED_{HowNet}^- \cap ED' \tag{3}$$

For the words in ED' that are not in the HowNet sentiment dictionary, artificial recognition can be used to determine the dictionary that these words are included in.

According to the constructed product dictionary, the sentiment orientations of each online review are recognized by using a sentiment analysis algorithm. Because the sentiment orientations of online reviews depend on the sentiment words in the online reviews and are affected by negative words in the online reviews, the following rules are followed in this study when the sentiment orientations of each online review are recognized. It includes (1) if one review only contains positive or negative sentiment words, then the sentiment orientation of this review is positive or negative; (2) if one review contains neither positive nor negative sentiment words, then the sentiment orientation of this review is neutral; (3) if one review contains not only positive or negative sentiment words but also negative words and the number of negative words is an odd number, then the sentiment orientation of this review is flipped.

Let $Z^j_{iv} = (Sn^j_{iv}, Su^j_{iv}, Sp^j_{iv})$ denote the indicator vector of the sentiment orientations of review ED^j_{iv} that correspond to e_j of product u_i, where $Sn^j_{iv}, Su^j_{iv}, Sp^j_{iv}$ denote the indicator values of negative, neutral, and positive sentiments of review ED^j_{iv}, respectively, and $Sn^j_{iv}, Su^j_{iv}, Sp^j_{iv} = 0$ or 1. Let $\overline{ED}_{Neg}$ denote the set of common Chinese negative words, wr^{j+}_{iv} denote the indicator variable of the intersections of ED^j_{iv} and ED^+, and wr^{j-}_{iv} denote the indicator variable of the intersections of ED^j_{iv} and ED^-. Let wr^{jNeg}_{iv} denote the score of the odd number of words in ED^j_{iv} that belong to $\overline{ED}_{Neg}$ and b^j_{ivu} denote the indicator value of the uth word in ED^j_{iv} that belongs to $\overline{ED}_{Neg}$. If $ED^j_{ivu} \in \overline{ED}_{Neg}$, then $b^j_{ivu} = 1$; otherwise, $b^j_{ivu} = 0$. Let ξ^{jNeg}_{iv} denote the indicator value of the number of words in ED^j_{iv} that belong to $\overline{ED}_{Neg}$ with an odd number, i.e.,

$$\xi^{jNeg}_{iv} = \begin{cases} 1, & \text{MOD}(\sum\limits_{u=1}^{q^j_{iv}} b^j_{ivu}, 2) = 1 \\ 0, & \text{Others} \end{cases} \tag{4}$$

where $\text{MOD}(\sum\limits_{u=1}^{q^j_{iv}} b^j_{ivu}, 2)$ denotes the remainder when $\sum\limits_{u=1}^{q^j_{iv}} b^j_{ivu}$ is divided by 2.

The sentiment orientation of ED^j_{iv} can be determined according to the constructed sentiment dictionary and the recognition rules of the sentiment orientation of online reviews, as described below.

Step 1: if $ED^j_{iv} = \varnothing$, then $Z^j_{iv} = (0, 0, 0)$; otherwise, turn to step 2;

Step 2: if $ED^j_{iv} \cap ED^+ \neq \varnothing$, then $wr^{j+}_{iv} \leftarrow 1$; otherwise, $wr^{j+}_{iv} \leftarrow 0$;

Step 3: if $ED^j_{iv} \cap ED^- \neq \varnothing$, then $wr^{j-}_{iv} \leftarrow 1$; otherwise $wr^{j-}_{iv} \leftarrow 0$;

Step 4: if $ED^j_{iv} \cap \overline{ED}_{Neg} \neq \varnothing$ and $\xi^{jNeg}_{iv} = 1$, then $wr^{jNeg}_{iv} \leftarrow 1$; otherwise, $wr^{jNeg}_{iv} \leftarrow 0$;

Step 5: if $wr^{j+}_{iv} = wr^{j-}_{iv}$, then $Z^j_{iv} = (0, 1, 0)$; if $wr^{j+}_{iv} = 1$, $wr^{j-}_{iv} = 0$, and $wr^{jNeg}_{iv} = 0$, or $wr^{j+}_{iv} = 0$, $wr^{j-}_{iv} = 1$, and $wr^{jNeg}_{iv} = 1$, then $Z^j_{iv} = (0, 0, 1)$; otherwise, $Z^j_{iv} = (1, 0, 0)$.

4.2. Transforming Sentiment Orientations of Index Parameters into Intuitionistic Fuzzy Soft Sets

Intuitionistic fuzzy soft set theory [49] is an effective tool when working with fuzzy and uncertain problems by combining the advantages of soft sets and intuitionistic fuzzy sets [52]. The advantages of soft sets are parameterization and flexibility, and the advantages of intuitionistic fuzzy sets are their effectiveness in solving uncertain problems. Intuitionistic fuzzy soft set theory fully takes account of decision makers' preferences and can reflect the degrees of support, opposition, and hesitation for some specific events when it is used to describe the object. Thus, intuitionistic fuzzy soft set theory can express the feature of the fuzziness of events more fully and more objectively. In order to select products while fully taking into account consumers' expectations, the sentiment orientations of the index parameters are transformed into intuitionistic fuzzy soft sets.

Let $R_{ij} = (\kappa^{neg}_{ij}, \kappa^{neu}_{ij}, \kappa^{pos}_{ij})$ denote the statistical vector of the sentiment orientations of reviews corresponding to e_j of product u_i, i.e.,

$$R_{ij} = (\sum_{v=1}^{q_i} Sn^j_{iv}, \sum_{v=1}^{q_i} Su^j_{iv}, \sum_{v=1}^{q_i} Sp^j_{iv}) \tag{5}$$

According to R_{ij}, the positive, negative, and neutral evaluation values of online reviews concerning each index parameter can be calculated as follows:

$$P_{ij}^{neg} = \frac{\kappa_{ij}^{neg}}{\kappa_{ij}^{neg} + \kappa_{ij}^{neu} + \kappa_{ij}^{pos}} \tag{6}$$

$$P_{ij}^{neu} = \frac{\kappa_{ij}^{neu}}{\kappa_{ij}^{neg} + \kappa_{ij}^{neu} + \kappa_{ij}^{pos}} \tag{7}$$

$$P_{ij}^{pos} = \frac{\kappa_{ij}^{pos}}{\kappa_{ij}^{neg} + \kappa_{ij}^{neu} + \kappa_{ij}^{pos}} \tag{8}$$

According to the feature of intuitionistic fuzzy numbers in decision-making problems [48,53], the sentiment orientations reflected in online reviews can be expressed perfectly by intuitionistic fuzzy numbers. Let $\chi_{ij} = (\mu_{ij}, \nu_{ij})$ denote voting concerning e_j of product u_i, where μ_{ij} and ν_{ij} denote the degrees of support and opposition, respectively. Meanwhile, π_{ij} denotes the degree of uncertainty. Therefore, in this paper, the reviews with a positive sentiment orientation are regarded as support votes, and the reviews with a negative sentiment orientation are regarded as negative votes. The positive and negative evaluation values of online reviews can be regarded as the degrees of support and opposition of product u_i concerning e_j. In view of the above, an intuitionistic fuzzy number $\chi_{ij} = (\mu_{ij}, \nu_{ij})$ can be constructed to express the performance of product u_i concerning e_j, and the evaluation matrix $\widetilde{\chi} = [\chi_{ij}]_{m\times n} = [(\mu_{ij}, \nu_{ij})]_{m\times n}$ $(i \in I, j = 1,2,\ldots,n)$ in the form of intuitionistic fuzzy numbers is further constructed, where μ_{ij} denotes the membership function of product u_i concerning e_j, ν_{ij} denotes the non-membership function of product u_i concerning e_j, π_{ij} is the hesitation function, and the calculation formulas of μ_{ij}, ν_{ij}, and π_{ij} are expressed as follows:

$$\mu_{ij} = P_{ij}^{pos} \tag{9}$$

$$\nu_{ij} = P_{ij}^{neg} \tag{10}$$

$$\pi_{ij} = P_{ij}^{neu} \tag{11}$$

Similarly, the evaluation matrix $\widetilde{\chi}_k = [\chi_{il}^k]_{m\times L_k} = [(\mu_{il}^k, \nu_{il}^k)]_{m\times L_k}$ of product u_i concerning e_l^k in the form of intuitionistic fuzzy numbers is constructed. According to Definition 7, $\widetilde{\chi} = [\chi_{ij}]_{m\times n}$ and $\widetilde{\chi}_k = [\chi_{il}^k]_{m\times L_k}$ can be transformed into intuitionistic fuzzy soft sets (F, E) and (F_k, E_k), i.e.,

$$F(e_j) = \left\{ (u_i, \chi_{ij}) \middle| u_i \in U \right\} = \left\{ (u_i, (\mu_{ij}, \nu_{ij})) \middle| u_i \in U \right\} \tag{12}$$

$$F_k(e_l^k) = \left\{ (u_i, \chi_{il}^k) \middle| u_i \in U \right\} = \left\{ (u_i, (\mu_{il}^k, \nu_{il}^k)) \middle| u_i \in U \right\} \tag{13}$$

4.3. Product Screening Considering Consumers' Expectations

According to the acceptable level $AL_l^k(s_l^k, t_l^k)$ of membership and non-membership regarding index parameter e_l^k given by consumer D_k, the acceptable level set $(F_k, E_k)_{(s,t)}$ concerning the intuitionistic fuzzy soft set (F_k, E_k) of consumer D_k can be defined, where $F_k^{(s,t)}(e_l^k) = \left\{ u_i \in U : \mu_{il}^k \geq s_l^k, \nu_{il}^k \leq t_l^k \right\}$ for $\forall e_l^k \in E_k$ [54], and $s_l^k, t_l^k \in [0,1]$. Let $(F_k, \widetilde{E}_k)$ denote the product soft set that conforms to the acceptable level regarding the index parameters of each consumer. In order to obtain the alternative product set that conforms to the acceptable levels of all consumers, the *uni-int* operator can be used to calculate $uni_y int_x((F_k, \widetilde{E}_k) \wedge (F_g, \widetilde{E}_g))$ between two soft sets, $k, g = 1, 2, \ldots, p$, $k \neq g$, i.e.,

$$uni_y int_x((F_k, \widetilde{E}_k) \wedge (F_g, \widetilde{E}_g)) = \underset{y \in \widetilde{E}_g}{\cup} (\underset{x \in \widetilde{E}_k}{\cap} (f_{\widetilde{E}_k \wedge \widetilde{E}_g}(x, y))) \tag{14}$$

where the approximate function $f_{\widetilde{E}_k \wedge \widetilde{E}_g}(x, y)$ of $(F_k, \widetilde{E}_k) \wedge (F_g, \widetilde{E}_g)$ is

$$f_{\widetilde{E}_k \wedge \widetilde{E}_g}(x, y) = f_{\widetilde{E}_k}(x) \cap f_{\widetilde{E}_g}(y) \tag{15}$$

Then, the product set that meets the needs of consumer D_k can be obtained, i.e.,

$$U_k = \overset{p}{\underset{g=1, k \neq g}{\cup}} uni_y int_x((F_k, \widetilde{E}_k) \wedge (F_g, \widetilde{E}_g)) \tag{16}$$

Further, the alternative product set U^* can be obtained by preliminary screening, i.e., the alternative product set that meets the needs of each consumer can be obtained, which is

$$U^* = \overset{p}{\underset{k=1}{\cap}} U_k \tag{17}$$

where $U^* = \{u_i | i \in I^*\}$, and I^* is the subscript set of alternative products, $I^* \subseteq I$.

4.4. Product Ranking Based on TODIM

The TODIM method was proposed by Gomes and Lima [55] and is a multi-attribute decision-making method based on prospect theory. The idea of the TODIM method is to calculate the dominance degrees of alternative products by comparing any two alternative products, and to calculate the overall dominance degree of each alternative product over other alternative products, thus ranking the alternative products according to their overall dominance degrees [56–58]. Compared with other decision methods, the TODIM method takes the risk preferences of decision makers into account and the calculation processes are simple. Therefore, in this study, the TODIM method is used to rank the alternative products based on the intuitionistic fuzzy soft sets of alternative products. According to the intuitionistic fuzzy soft set of alternative product u_i, $i \in I^*$, the score function value [59] of alternative product u_i for index e_j is

$$S_i(F(e_j)) = \frac{\mu_{ij} - \nu_{ij} + 1 - \ln(1 + \pi_{ij})}{2} \tag{18}$$

Then, according to the score function values, the scores of any two alternative products concerning each index are compared, and the gain–loss matrix $\widetilde{S}_j = [s_{ih}^j]_{m \times n}$ can be built, $i \in I^*$, where s_{ih}^j denotes the gain–loss value between alternative products for each index, i.e.,

$$s_{ih}^j = \begin{cases} d(\chi_{ij}, \chi_{hj}), & S_i(F(e_j)) > S_h(F(e_j)) \\ 0, & S_i(F(e_j)) = S_h(F(e_j)) \\ -d(\chi_{ij}, \chi_{hj}), & S_i(F(e_j)) < S_h(F(e_j)) \end{cases} \tag{19}$$

where $d(\chi_{ij}, \chi_{hj}) = \frac{1}{2}(\left|\mu_{ij} - \mu_{hj}\right| + \left|\nu_{ij} - \nu_{hj}\right| + \left|\pi_{ij} - \pi_{hj}\right|)$, $i \neq h$. If $S_i(F(e_j)) > S_h(F(e_j))$, then alternative product u_i is gainful relative to alternative product u_h. If $S_i(F(e_j)) = S_h(F(e_j))$, then alternative product u_i is equivalent to alternative product u_h. If $S_i(F(e_j)) < S_h(F(e_j))$, then alternative product u_i is loss-making relative to alternative product u_h, $i \in I^*$.

Then, the relative weight w_{jr} of index parameter e_j relative to e_r is calculated [60], i.e.,

$$w_{jr} = \frac{w_j}{w_r} \tag{20}$$

where $w_r = \max_{1 \le j \le n}\{w_j\}$. In order to avoid the second uncertainty caused by the simple subjective weighting method, the determination method of weight w_j of index parameter e_j based on intuitionistic fuzzy soft set entropy [44] is used:

$$w_j = \frac{1 - H(F, e_j)}{n - \sum_{j=1}^{n} H(F, e_j)} \tag{21}$$

and

$$H(F, e_j) = \frac{1}{2m^*} \sum_{i \in I^*} (2 - \mu_{ij} - \nu_{ij} - \left|\mu_{ij} - \nu_{ij}\right|) \tag{22}$$

where m^* denotes the number of alternative products.

According to the relative weight w_{jr} and the gain–loss value s_{ih}^{j}, the dominance degree matrix $\Phi_j = [\varphi_j(u_i, u_h)]_{m^* \times m^*}$ of the alternative products in pairs for each index parameter can be built, where $\varphi_j(u_i, u_h)$ denotes the dominance degree of alternative product u_i relative to alternative product u_h concerning index parameter e_j. The calculation formula of $\varphi_j(u_i, u_h)$ is

$$\varphi_j(u_i, u_h) = \begin{cases} \sqrt{\frac{s_{ih}^{j} \cdot w_{jr}}{\sum_{j=1}^{n} w_{jr}}}, & s_{ih}^{j} > 0 \\ 0, & s_{ih}^{j} = 0 \\ -\frac{1}{\theta}\sqrt{\frac{-s_{ih}^{j} \cdot \sum_{j=1}^{n} w_{jr}}{w_{jr}}}, & s_{ih}^{j} < 0 \end{cases} \tag{23}$$

where θ is the loss attenuation coefficient, $\theta > 0$, and the smaller θ, the more consumers tend to display loss aversion. The specific value of θ can be determined by the attitude toward risk of decision makers in practice, $i, h \in I^*$, $i \neq h$.

Further, to aggregate the dominance degree $\varphi_j(u_i, u_h)$ of alternative product u_i relative to alternative product u_h concerning each index parameter, the overall dominance degree $\varphi(u_i, u_h)$ between two alternative products can be obtained, i.e.,

$$\varphi(u_i, u_h) = \sum_{j=1}^{n} \varphi_j(u_i, u_h) \tag{24}$$

Based on this, the overall dominance degree of each alternative product over other alternative products is calculated, i.e.,

$$\vartheta(u_i) = \frac{\sum\limits_{h \in I^*} \varphi(u_i, u_h) - \min_i\{\sum\limits_{h \in I^*} \varphi(u_i, u_h)\}}{\max_i\{\sum\limits_{h \in I^*} \varphi(u_i, u_h)\} - \min_i\{\sum\limits_{h \in I^*} \varphi(u_i, u_h)\}} \tag{25}$$

Obviously, the higher $\vartheta(u_i)$ is, the better alternative product u_i will be. Therefore, a ranking of the alternative products can be obtained according to the value of $\vartheta(u_i)$.

5. Case Study

In this section, a digital camera selection problem is provided to further express the application of the proposed method. The ZS Media company plans to purchase a batch of digital cameras with a unit price of around 15,000 CNY. To meet the needs of the photography department, the index parameters $E = \{e_1, e_2, \ldots, e_7\}$ of digital cameras are investigated, where $e_1 \sim e_7$ are in order as follows: the camera is cost-effective, the lens is practical, it allows high-definition imaging, it is easy to operate, it can focus quickly, it has fine workmanship, and the color is realistic. The index parameters considered by 3 senior photographers (D_1, D_2, D_3) in the photography department are $E_1 = \{e_1, e_2, e_3\}$, $E_2 = \{e_3, e_4, e_5\}$, $E_3 = \{e_5, e_6, e_7\}$, and the corresponding expectations of each photographer regarding the index parameters are $AL_1^1(0.85, 0.1)$, $AL_2^1(0.5, 0.2)$, $AL_3^1(0.85, 0.1)$, $AL_3^2(0.9, 0.05)$, $AL_4^2(0.85, 0.1)$,

$AL_5^2(0.8, 0.15)$, $AL_5^3(0.75, 0.2)$, $AL_6^3(0.85, 0.15)$, $AL_7^3(0.85, 0.1)$. Eight digital cameras are considered in this selection problem after investigating the digital camera market, i.e.,

u_1: SONY A7III (28–70 mm);
u_2: SONY A7C (28–60 mm)
u_3: Nikon Z6 (24–70 mm);
u_4: Panasonic Lumix S5 (20–60 mm);
u_5: Canon 6D Mark II (24–70 mm);
u_6: Canon EOS RP (24–240 mm);
u_7: Nikon Z5 (24–70 mm);
u_8: Canon EOS 90D (18–200 mm).

To help this company to make a purchase decision, the 8 digital cameras should be ranked according to the expectations of the photographers and online reviews. Firstly, according to the rules that the post time is from 2021 to 2022 and the word count of online reviews is greater than or equal to 30, the online reviews $R_i = \{R_{i1}, R_{i2}, \ldots, R_{iq_i}\}$ of the 8 digital cameras are extracted by the Octopus collector (http://www.bazhuayu.com/ (accessed on 7 June 2023)) from Zhongguancun Online (ZOL, https://www.zol.com.cn/ (accessed on 7 June 2023)). Then, R_i is pretreated and the word set $ED_{iv} = \left\{ED_{iv}^1, ED_{iv}^2, \ldots, ED_{iv}^{q_{iv}}\right\}$ of each online review can be obtained, $i = 1, 2, 3, 4, 5, 6, 7, 8$, $v = 1, 2, \cdots, q_i$, $q_1 = 447$, $q_2 = 311$, $q_3 = 376$, $q_4 = 273$, $q_5 = 320$, $q_6 = 423$, $q_7 = 562$, $q_8 = 540$. Taking u_1 as an example, the pretreatment results of the online reviews are presented in Table 1.

Table 1. The pretreatment results of online reviews of u_1.

Online Reviews	Pretreatment Results
R_{11}	相机/n外观/n包装/v好/a, /x外形/n比较/d轻薄/a, /x成像/v效果/n好/a, /x像素/n高/a, /x反应/v速度/n快/a, /x便携性/b不错/a, /x屏幕/n力/n不错/a, /x挺/d好/a, /x推荐/v大家/n购买/v./x (The camera has a well packaged appearance, the appearance is relatively thin, the imaging effect is good, the pixel is high, the response is fast, the portability is good, the screen power is good, it is very good, we recommend you to buy.)
R_{12}	产品/n包装/n好/a, /x外形/n很/zg喜欢/v, /x小巧/n, /x手感/n不错/a, /x成像/v效果/n反应/v速度/n快/a, /x便携性/b不错/a./x (The product is well packaged, I really like its appearance, small and compact, with a good touch, fast imaging response, and good portability.)
⋮	⋮
R_{1447}	人生/n中/f第一台/m微单/a相机/d, /x单反相机/n小巧/n, /x按键/n布局/n比较/d方便/a, /x很/zg推荐/v购买/v./x (The first micro-single camera in life, SLR camera compact, button layout is more convenient, it is recommended to buy.)

Then, the review information ED_{iv}^j for the different index parameters of each online review is recognized. The nouns or verbs are extracted from index parameters $E = \{e_1, e_2, \ldots, e_7\}$, and the corresponding words of $e_1 \sim e_7$ are "cost performance", "lens", "imaging", "operation", "focusing", "workmanship", and "color". Taking the first review R_{11} of camera u_1 as an example, only reviews about imaging (c_3) are included in R_{11}, and then the adjectives, nouns, verbs, and adverbs between two adjacent punctuation marks are extracted from R_{11} including imaging (c_3), and the review information corresponding to imaging (c_3) in this online review can be obtained, i.e., ED_{11}^3 ={好/a}.

According to Equations (1)–(3), the positive sentiment dictionary and negative sentiment dictionary for the digital cameras are built, which are shown in Table 2.

Table 2. Some sentiment words in the sentiment dictionary.

ED^+	ED^-
好(good), 快(fast), 方便(convenient), 不错(not bad), 细腻(delicate), 一流(first-class), 艳丽(gorgeous), 完美(perfect), 合适(suitable), 高(high), 强大(powerful), 满意(satisfactory) ···	差(poor), 不行(not good), 复杂(complex), 不准(inaccurate), 重(heavy), 弱(weak), 落伍(outdated), 烂(rotten), 垃圾(rubbish), 慢(slow), 低(low), 不足(insufficient) ···

According to Equation (4) and steps 1–5, the indicator vector $Z_{iv}^j = (Sn_{iv}^j, Su_{iv}^j, Sp_{iv}^j)$ of the sentiment orientations of each online review can be determined. Taking ED_{11}^1 as an example, the determination of $Z_{11}^1 = (Sn_{11}^1, Su_{11}^1, Sp_{11}^1)$ is shown as follows.

Step 1: because $ED_{11}^1 \neq \varnothing$, turn to step 2;

Step 2: because $ED_{11}^1 \cap ED^+ \neq \varnothing$, then $wr_{11}^{1+} \leftarrow 1$;

Step 3: because $ED_{11}^1 \cap ED^- = \varnothing$, then $wr_{11}^{1-} \leftarrow 0$;

Step 4: because $ED_{11}^1 \cap \overline{ED}_{Neg} = \varnothing$, then $wr_{11}^{1Neg} \leftarrow 0$;

Step 5: because $wr_{11}^{1+} = 1$, $wr_{11}^{1-} = 0$, and $wr_{11}^{1Neg} = 0$, then $Z_{11}^1 = (0, 0, 1)$.

According to Equations (5)–(13), the positive evaluation value P_{ij}^{pos}, the negative evaluation value P_{ij}^{neg}, and the neutral evaluation value P_{ij}^{neu} of each digital camera concerning each index parameter can be calculated, and, according to Equations (9)–(13), the intuitionistic fuzzy soft sets (F, E) and (F_k, E_k) of each digital camera concerning each index parameter can be determined; (F, E) is shown in Table 3.

Table 3. Intuitionistic fuzzy soft set (F, E).

Digital Cameras	Index Parameters						
	e_1	e_2	e_3	e_4	e_5	e_6	e_7
u_1	(0.9452,0.0274)	(0.4487,0.2949)	(0.9109,0.0297)	(0.6500,0.2500)	(0.8493,0.1096)	(0.8438,0.1562)	(0.7692,0.2308)
u_2	(0.8750,0.0938)	(0.5873,0.0794)	(0.9583,0.0000)	(0.7143,0.2381)	(0.9577,0.0141)	(0.8235,0.1176)	(0.5714,0.4286)
u_3	(0.9762,0.0079)	(0.7415,0.0748)	(0.9131,0.0156)	(0.9302,0.0233)	(0.8750,0.0893)	(0.9538,0.0000)	(0.9714,0.0286)
u_4	(0.9730,0.0000)	(0.5814,0.2674)	(0.9623,0.0094)	(0.9111,0.0222)	(0.6528,0.2361)	(0.9138,0.0862)	(0.9802,0.0000)
u_5	(0.7347,0.1224)	(0.5556,0.1111)	(0.9747,0.0000)	(0.9286,0.0714)	(0.9118,0.0588)	(0.8929,0.1071)	(0.9545,0.0455)
u_6	(0.8519,0.0926)	(0.5000,0.2037)	(0.8718,0.0385)	(0.9310,0.0000)	(0.8421,0.1579)	(0.8571,0.1071)	(0.8571,0.0952)
u_7	(0.9441,0.0335)	(0.6353,0.1255)	(0.9333,0.0095)	(0.8835,0.0291)	(0.8347,0.1405)	(0.9828,0.0000)	(0.9583,0.0000)
u_8	(0.9286,0.0714)	(0.5455,0.0909)	(0.9245,0.0283)	(0.8519,0.0370)	(0.9130,0.0870)	(0.9630,0.0370)	(0.9333,0.0000)

Then, according to the expectations of each photographer regarding each index parameter, the soft sets $(F_1, \widetilde{E}_1)$, $(F_2, \widetilde{E}_2)$, and $(F_3, \widetilde{E}_3)$ that conform to the acceptable level concerning the index parameters of each photographer can be built, i.e.,

$$(F_1, \widetilde{E}_1) = \{(e_1, \{u_1, u_2, u_3, u_4, u_6, u_7, u_8\}), (e_2, \{u_2, u_3, u_5, u_7, u_8\}), (e_3, \{u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8\})\},$$
$$(F_2, \widetilde{E}_2) = \{(e_3, \{u_1, u_2, u_3, u_4, u_5, u_7, u_8\}), (e_4, \{u_3, u_4, u_5, u_6, u_7, u_8\}), (e_5, \{u_1, u_2, u_3, u_5, u_7, u_8\})\},$$
and $$(F_3, \widetilde{E}_3) = \{(e_5, \{u_1, u_2, u_3, u_5, u_6, u_7, u_8\}), (e_6, \{u_3, u_4, u_5, u_6, u_7, u_8\}), (e_7, \{u_3, u_4, u_5, u_6, u_7, u_8\})\}.$$

According to Equations (14) and (15), the product operations $\wedge$ between two soft sets are performed and the set of digital cameras can be obtained as follows.

$uni_y int_x((F_1, \widetilde{E}_1) \wedge (F_2, \widetilde{E}_2)) = \bigcup_{y \in \widetilde{E}_2} (\bigcap_{x \in \widetilde{E}_1} (f_{\widetilde{E}_1 \wedge \widetilde{E}_2}(x, y))) = \cup\{\cap\{\{u_1, u_2, u_3, u_4, u_7, u_8\}, \{u_2, u_3, u_5, u_7, u_8\}, \{u_1, u_2, u_3, u_4, u_5, u_7, u_8\}\}, \cap\{\{u_3, u_4, u_6, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}, \{u_3, u_4, u_5, u_6, u_7, u_8\}\}, \cap\{\{u_1, u_2, u_3, u_7, u_8\}, \{u_2, u_3, u_5, u_7, u_8\}, \{u_1, u_2, u_3, u_5, u_7, u_8\}\}\} = \cup\{\{u_2, u_3, u_7, u_8\}, \{u_3, u_7, u_8\}, \{u_2, u_3, u_7, u_8\}\} = \{u_2, u_3, u_7, u_8\};$
$uni_y int_x((F_1, \widetilde{E}_1) \wedge (F_3, \widetilde{E}_3)) = \bigcup_{y \in \widetilde{E}_3} (\bigcap_{x \in \widetilde{E}_1} (f_{\widetilde{E}_1 \wedge \widetilde{E}_3}(x, y))) = \cup\{\cap\{\{u_1, u_2, u_3, u_6, u_7, u_8\}, \{u_2, u_3, u_5, u_7, u_8\}, \{u_1, u_2, u_3, u_5, u_6, u_7, u_8\}\}, \cap\{\{u_3, u_4, u_6, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}, \{u_3, u_4, u_5, u_6, u_7, u_8\}\}, \cap\{\{u_3, u_4, u_6, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}, \{u_3, u_4, u_5, u_6, u_7, u_8\}\}\} = \cup\{\{u_2, u_3, u_7, u_8\}, \{u_3, u_7, u_8\}, \{u_3, u_7, u_8\}\} = \{u_2, u_3, u_7, u_8\};$
$uni_y int_x((F_2, \widetilde{E}_2) \wedge (F_3, \widetilde{E}_3)) = \bigcup_{y \in \widetilde{E}_3} (\bigcap_{x \in \widetilde{E}_2} (f_{\widetilde{E}_2 \wedge \widetilde{E}_3}(x, y))) = \cup\{\cap\{\{u_1, u_2, u_3, u_5, u_7, u_8\}, \{u_3, u_5, u_6, u_7, u_8\}, \{u_1, u_2, u_3, u_5, u_7, u_8\}\}, \cap\{\{u_3, u_4, u_5, u_7, u_8\}, \{u_3, u_4, u_5, u_6, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}\}, \cap\{\{u_3, u_4, u_5, u_7, u_8\}, \{u_3, u_4, u_5, u_6, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}\}\} = \cup\{\{u_3, u_5, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}, \{u_3, u_5, u_7, u_8\}\} = \{u_3, u_5, u_7, u_8\}.$

Similarly, the following can be obtained.

$$\begin{aligned} &uni_y int_x((F_2, \widetilde{E}_2) \wedge (F_1, \widetilde{E}_1)) = \{u_3, u_5, u_7, u_8\}, \\ &uni_y int_x((F_3, \widetilde{E}_3) \wedge (F_1, \widetilde{E}_1)) = \{u_3, u_5, u_6, u_7, u_8\}, \\ &uni_y int_x((F_3, \widetilde{E}_3) \wedge (F_2, \widetilde{E}_2)) = \{u_3, u_5, u_6, u_7, u_8\}. \end{aligned}$$

According to Equation (16), the set of digital cameras that meets the needs of each photographer can be obtained, i.e.,

$$\begin{aligned} U_1 &= \cup\{uni_y int_x((F_1, \widetilde{E}_1) \wedge (F_2, \widetilde{E}_2)), uni_y int_x((F_1, \widetilde{E}_1) \wedge (F_3, \widetilde{E}_3))\} = \{u_2, u_3, u_7, u_8\}, \\ U_2 &= \cup\{uni_y int_x((F_2, \widetilde{E}_2) \wedge (F_1, \widetilde{E}_1)), uni_y int_x((F_2, \widetilde{E}_2) \wedge (F_3, \widetilde{E}_3))\} = \{u_3, u_5, u_7, u_8\}, \\ U_3 &= \cup\{uni_y int_x((F_3, \widetilde{E}_3) \wedge (F_1, \widetilde{E}_1)), uni_y int_x((F_3, \widetilde{E}_3) \wedge (F_2, \widetilde{E}_2))\} = \{u_3, u_5, u_6, u_7, u_8\}. \end{aligned}$$

According to Equation (17), the alternative digital camera set U^* can be obtained by preliminary screening, i.e., $U^* = \bigcap_{k=1}^{3} U_k = \{u_3, u_7, u_8\}$. According to Equations (18) and (19), the gain–loss matrix $\widetilde{S}_j = [s_{ih}^j]_{3 \times 7}$ can be built, which is shown in Table 4.

Table 4. The gain–loss matrix.

Index Parameter	The Alternative Digital Camera Set		
	u_3/u_7	u_3/u_8	u_7/u_8
e_1	0.0321	0.0635	0.0379
e_2	0.1062	0.1960	0.1244
e_3	−0.0202	−0.0241	0.0188
e_4	0.0467	0.0783	0.0316
e_5	0.0512	−0.0380	−0.0783
e_6	−0.0290	−0.0462	0.0370
e_7	0.0417	0.0667	0.0250

According to Equations (20)–(22), the relative weight w_{jr} of index parameter e_j relative to e_r is calculated, which is shown in Table 5.

Table 5. The weight and relative weight of index parameters.

	Index Parameter						
	e_1	e_2	e_3	e_4	e_5	e_6	e_7
w_j	0.1532	0.1034	0.1490	0.1434	0.1410	0.1560	0.1540
w_{jr}	0.9821	0.6628	0.9551	0.9192	0.9038	1.0000	0.9872

According to Equation (23), the dominance degree $\varphi_j(u_i, u_h)$ of alternative digital camera u_i relative to alternative digital camera u_h concerning index parameter e_j is calculated, where $\theta = 1$. The dominance degree matrix $\Phi_j = [\varphi_j(u_i, u_h)]_{m^* \times m^*}$ is shown as follows.

$$\Phi_1 = \begin{bmatrix} 0.0000 & 0.0701 & 0.0986 \\ -0.4577 & 0.0000 & 0.0762 \\ -0.6438 & -0.4974 & 0.0000 \end{bmatrix}$$

$$\Phi_2 = \begin{bmatrix} 0.0000 & 0.1048 & 0.1424 \\ -1.0134 & 0.0000 & 0.1134 \\ -1.3768 & -1.0969 & 0.0000 \end{bmatrix}$$

$$\Phi_3 = \begin{bmatrix} 0.0000 & -0.3682 & -0.4022 \\ 0.0549 & 0.0000 & 0.0529 \\ 0.0599 & -0.3552 & 0.0000 \end{bmatrix}$$

$$\Phi_4 = \begin{bmatrix} 0.0000 & 0.0818 & 0.1060 \\ -0.5707 & 0.0000 & 0.0673 \\ -0.7389 & -0.4694 & 0.0000 \end{bmatrix}$$

$$\Phi_5 = \begin{bmatrix} 0.0000 & 0.0850 & -0.5191 \\ -0.6026 & 0.0000 & -0.7452 \\ 0.0732 & 0.1051 & 0.0000 \end{bmatrix}$$

$$\Phi_6 = \begin{bmatrix} 0.0000 & -0.4312 & -0.5442 \\ 0.0673 & 0.0000 & 0.0760 \\ 0.0849 & -0.4870 & 0.0000 \end{bmatrix}$$

$$\Phi_7 = \begin{bmatrix} 0.0000 & 0.0801 & 0.1013 \\ -0.5204 & 0.0000 & 0.0620 \\ -0.5204 & -0.4029 & 0.0000 \end{bmatrix}$$

According to Equations (24) and (25), the overall dominance degree $\vartheta(u_i)$ of alternative digital camera u_i over other alternative digital cameras is calculated, i.e., $\vartheta(u_3) = 1.0000$, $\vartheta(u_7) = 0.6116$, $\vartheta(u_8) = 0.0000$. Based on the values of $\vartheta(u_i)$, the ranking of alternative digital cameras can be obtained, i.e., $u_3 \succ u_7 \succ u_8$.

In order to further illustrate the feasibility and effectiveness of the proposed method, it is compared with the method proposed by Liu et al. [21]. With the method provided by Liu et al. [21], the digital camera selection problem in this numerical analysis can be solved and the relative dominance degrees of alternative digital cameras can be calculated as $\Phi(u_1) = -0.8460$, $\Phi(u_2) = -0.6360$, $\Phi(u_3) = 0.8750$, $\Phi(u_4) = 0.1060$, $\Phi(u_5) = -0.0310$, $\Phi(u_6) = -0.3750$, $\Phi(u_7) = 0.6250$, $\Phi(u_8) = 0.3000$. According to the values of the relative dominance degrees, the ranking of alternative digital cameras can be determined as $u_3 \succ u_7 \succ u_8 \succ u_4 \succ u_5 \succ u_6 \succ u_2 \succ u_1$. It is obvious that the two methods have the same ranking results for alternative digital cameras; for both, the optimal selection is u_3. However, it should be pointed out that although the results are the same, there exist some differences between the proposed method in this study and the method provided by Liu et al. [21]. In the process of decision making, Liu et al.'s [21] method ranks the alternative digital cameras entirely on the basis of online reviews, while our method first screens the digital cameras according to online reviews and the expectations of multiple consumers and then ranks the alternative digital cameras that pass the screening, so the results obtained with the proposed method in this study not only meet the needs of the consumer group but also have good overall performance. In addition, in the study of Liu et al. [21], consumers were believed to be completely rational, while, in a real purchase decision, it is difficult for consumers to be completely rational. Compared with the study of Liu et al. [21], this study has considered the consumers' psychological behaviors, including reference dependence and loss aversion, which is consistent with the actual situation.

Moreover, in the determination of the weights of the index parameters, the weights were provided directly by consumers in the study of Liu et al. [21], while this study has proposed the weights based on the entropy theory of information, which can largely avoid the interference of subjective factors.

6. Conclusions

In this study, we developed a product selection method considering multiple consumers' expectations and online reviews. In this method, the sentiment orientations of each online review concerning product index parameters are recognized using the dictionary-based sentiment analysis algorithm, and then the evaluation values of the sentiment orientations for product index parameters can be expressed by intuitionistic fuzzy numbers and be transformed into intuitionistic fuzzy soft sets. Further, the alternative product set can be obtained according to multiple consumers' expectations. Finally, the ranking of the alternative products can be obtained using the TODIM method. The contributions of this paper are discussed as follows.

Firstly, this paper formulates a new problem in product selection considering multiple consumers' expectations and online reviews. In the problem, the factors that affect purchase decisions are considered, such as the product index parameters and expectations considered by consumers, online reviews, and the weights of the index parameters. The problem has a number of practical applications in real life. Moreover, a new resolution process for the product selection problem is proposed. The process of product selection is divided into two stages, screening and ranking, which can better save time in making purchase decisions and improve the efficiency and accuracy of the ranking of the alternative products. This solution process can lay a good foundation for further research on product selection through online reviews.

Secondly, this paper fully considers the subjective preferences of consumers and the positive, neutral, and negative sentiment orientations for each index parameter. An intuitionistic fuzzy soft set is used to express the different sentiment orientations of consumers regarding the index parameters, which combines the advantages of the parameterization and flexibility of a soft set with the effectiveness of an intuitionistic fuzzy set to deal with uncertain problems, and it can reflect more accurately the different sentiment orientations included in online reviews and then reduces the uncertainty in decision making. This is a new idea for the processing and integration of the vast sentiment orientations contained in online reviews.

Thirdly, for the common group-buying situation, in reality, the differences in the index parameters highlighted by multiple consumers are considered. Meanwhile, the expectations and psychological behaviors of consumers regarding the index parameters are considered, which is in line with the real decision-making processes of consumers in product selection and can help consumers to select products that match their preferences.

In addition, the method proposed in this paper is of clear conception and great maneuverability in the practical situation and provides a feasible method basis to solve the problem of product purchase decision making based on online reviews in the era of big data.

Future research will focus on the development of a decision support system in which the proposed method is embedded, which can make the use of the proposed method more convenient and efficient. In addition, only online reviews in the form of text were considered in this study, so it is necessary to consider online reviews in other forms in future research—for example, online ratings, pictures, emotion icons, and so on.

Author Contributions: Conceptualization, P.C.; Methodology, J.Z.; Data curation, P.C. and J.Z.; Writing—original draft, P.C.; Writing—review and editing, M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Social Science Planning Fund Project of Liaoning Province (Project No. L21BGL056).

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

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